University of Nottingham

L14010 Dissertation

Summer Term 2010

Stock Market Linkages - A Cointegration Approach

by Kilian Heilmann
(Student ID: 4099441)

Dissertation Supervisor: Steve Leybourne

Word Count: 14,574

This Dissertation is presented in part fulfilment of the requirement for the completion of a MSc Economics and Econometrics in the School of Economics, University of Nottingham. The work is the sole responsibility of the candidate.

Acknowledgements

I want to thank my supervisor, Professor Steve Leybourne, for his helpful advice and guidance, my friends [redacted] and [redacted] for all the hours spent together in library, my girlfriend [redacted] for her endless energy she gave to me, and all others who contributed to this dissertation. This work would not have been possible without their invaluable support.

Abstract

This dissertation investigates the linkages between stock markets by applying the cointegration framework developed by Engle and Granger (1987) on weekly data in a system of eight Asian stock price indices and the American S&P 500 index in local currencies. Performing pairwise Cointegration Regression Augmented Dickey Fuller tests does not suggest much evidence for long-run relationships between the stock indices. Applying the Johansen (1988) cointegration test on the whole system instead cleary indicates the existence of at least one cointegrating vector. The Vector Error Correction Model reveals that the US market is both strongly influential for the Asian markets in both the short and long run, with Korea being the regional leader. Accounting for a structural break using the Gregory and Hansen (1996) cointegration test reveals long-run equilibria that remained undetected by the CRADF. Further analysis suggests that the Asian financial crisis of 1997/1998 significantly changed the cointegration relationship between some countries, most notably between the US and Japan. Controlling for different stock index denomination shows that the results are mostly robust to a change to a common US dollar denomination.

Contents

List of Tables

List of Figures

1 Introduction

With the financial crisis of 2007 triggered by massive write-offs in the American subprime sector, it has become clear that today's equity markets across the world are no longer national markets. Not only in the US, but worldwide stock indices dropped dramatically with investors and stock traders in Tokyo, London and New York waiting for new announcements given by listed companies and adjusting their portfolio according to news from other markets. This indicates how much international stock markets have become connected among each other and how much they depend on their counterparts.

While these interactions between stock markets have been approved, a more critical question arises for both economic researchers and investors: Are these linkages only important in the short run or are there even long-run equilibrium relationships between stock markets? Equilibria that allow investors and researchers to use information about one market to predict the performance of another in the long run? Using the cointegration framework developed by Granger (1981) and subsequently enhanced by others allows to model and test for such a long-run relationship.

Whether stock markets are cointegrated or not is an important question for both financial economic theory and practical asset management. Regarding finance theory, if the efficient market hypothesis (EMH) holds in any of its versions, then stock returns should not be predictable using publicly available data such as index prices of other markets. This excludes any adjustment over time between two stock markets. Yet if there is a cointegration relationship between stock markets, the EMH is violated as one market contains information about the other which helps to predict its future value.

Furthermore, stock market cointegration has relevant implications for financial investors. Portfolio theory claims that investors should diversy their investment across assets provided the returns are not perfectly correlated. If there are positive long-run relationships between different markets, the advantage of international diversification is limited. Stock markets which share a common stochastic trend will generate similar returns in the long run. With comovements among different stock exchanges, losses in one market cannot be compensated by gains in the other. Stock market cointegration effectively reduces the number of independent assets available for the investor to hedge his risk.

The aim of this dissertation is to formally analyse and test for cointegration relationships in a system of eight East and Southeast Asian as well as the US stock markets using the cointegration framework. Special focus lies on the existence of a structrual break caused by the Asian financial crisis of 1997/1998. It rests on previous studies by Yang et al. (2002) and Wong et al. (2004) examining the cointegration structure of Asia's equity markets. These studies have recognized the impact of the Asian crisis on stock market interaction and estimated models for different periods. This dissertation tries to enhance the analysis of the Asian crisis by formally testing for cointegration under a structural break using the method of Gregory and Hansen (1996) on a new dataset covering the period 1995-2010.

It follows previous studies in using both the Engle and Granger (1987) as well as Johansen (1988) approaches to cointegration. Estimating a vector error correction model (VECM) will provide an insight into long-run and short-run stock market linkages in the system of nine stock markets. Granger causality tests and impulse response analysis will investigate short-run adjustment The results suggest that there are long-run equilibria between the Asian stock markets and that the Asian crisis indeed had a significant influence on at least some of the cointegration patterns in the sample.

This work is structured as follows. Chapter two review the relevant literature on stock market cointegration. Section three will give an overview of the used cointegration methodology including a cointegration test under structural breaks. Section four comments on the dataset. Chapter five presents the empirical results and performs robustness checks. Finally, section six provides concluding remarks.

2 Literature Review

Early studies of stock market interdependences date back to the early seventies. Authors such as Granger and Morgenstern (1970), Ripley (1973) or Panto et al. (1976) investigated short-run linkages using correlation analysis. With the emergence of the cointegration framework first suggested by Granger (1981) and consequently developed by Granger and Weiss (1983) and Engle and Granger (1987), the methodology of stock market linkages improved. Along with the Autoregressive Conditional Heteroskedasticity (ARCH) approach developed by Engle (1982) and extended by Bollerslev (1986), cointegration has now become the main tool in analysing the relationship between stock markets. Further methodological improvements by Johansen (1988, 1991) eased the treatment of multivariate cointegration and provided a unified approach to estimation and testing.

Kasa (1992) first used Johansen's cointegration test to study the linkages of stock markets. Using a long VAR specification, the author finds strong evidence for a single common trend in the markets of the US, Japan, Germany, Britain and Canada for the period 1974-1990. Corhay et al. (1993) investigate European stock markets between 1975-1991 and also provide empirical evidence for long-run equilibria. In a broader study of 16 markets, Blackman et al. (1994) find cointegration relationships for the 1980s. However, the study by Koop (1994) using Bayesian methods rejects a common stochastic trend between the stock markets of the five aforementioned countries. Fu and Pagani (2010) revisit Kasa's (1992) result and use more accurate small sample corrections on the same data. Though the evidence for cointegration is weaker than in the original paper, the authors still find a cointegration relationship.

The focus of stock market cointegration studies subsequentially shifted from more established to the emerging markets especially those of Asia. The rise of East and Southeast Asian stock markets due to financial deregulation in the early 1990s gave way to numerous studies of Asia's newly industrialized countries (NIC). Masih and Masih (1997) investigate the linkages of Taiwan, Hong Kong, Singapore and South Korea with the mature markets of Japan, USA, the UK and Germany and find evidence for a cointegration relationship.

Maysami and Koh (2000) observe a cointegration relationship between the markets of Singapore, Japan and the US. The results of Sheng and Tu (2000) in contrast do not suggest a statistically significant cointegration vector for Asian stock markets. Other studies on emerging markets include Chen et al. (2000) find evidence for cointegration among a system of six Latin American markets.

Yang, Kolari and Min (2002) investigated the Asian inancial crisis and find evidence for changing degrees of cointegration. Estimating the vector error correction for different periods, they find that the markets move closer together in the post-crisis period. Wong et al. (2004) also conclude that market linkages in Asia intensified with the crisis of 1997. Lim (2007) approves this results for the ASEAN[1] countries.

The analysis of stock market linkages improved with further methodological achievements. Gregory and Hansen (1996) developed a residual-based test for cointegration when a single structural break is present in the data. Applications of this method on the issue of stock market cointegration are for example Siklos and Ng (2001) who find that the 1987 stock market crash and the Second Gulf War (1991) were significant break points in the cointegration relationship. Fernandez and Sosvilla (2001) are unable to find cointegration between Asian markets using convential tests, but find long-run relationships for some countries when accounting for a structural break. Voronkova (2004) finds extensive previously undetected linkages of Central European stock markets with their mature counterparts in Europe and the US using the Gregory and Hansen cointegration test.

[1] Association of Southeast Asian Nations.

3 Methodology

3.1 The Cointegration Framework

The concept of cointegration rests on the groundbreaking works of Granger (1981) and Engle and Granger (1987) which deal with the relationship between non-stationary time series sharing a common stochastic trend. Suppose there are two time series processes which both contain a unit root. Even though the two series can wander arbitrarily, there might be some economic forces which tie them together and establish some kind of long-run equilibrium. This relationship is very common for economic data such as income and consumption or interest rates at different horizons. Modelling this long-run relationship by econometric methods and providing a unified framework for estimation and testing is the great methodological contribution of Clive Granger and Robert Engle which will now be presented formally.

Suppose there is a time series x_t which is integrated of order one, such that its differences are stationary. The Wold representation theorem states that every covariance-stationary process, which includes autoregressive moving average (ARMA) processes, can be written as an infinite MA process of its innovation process. Therefore the differences of x_t can be expressed as

$$\Delta x_t = \sum_{j=0}^{\infty} c_j \; \epsilon_{t-j} \tag{1}$$

where it is required that the series c_j is absolutely summable, such that $\sum_{j=0}^{\infty} c_j \leq \infty$.

Writing equation (1) in a multivariate setting, where x_t is a $(k \times 1)$ vector and $C(L)$ is a matrix polynomial of the form $C(L) = C_0 + C_1 L + C_2 L^2 + \cdots$ with its first term equal to the $(k \times k)$ identity matrix such that $C(0) = I_k$, yields

$$\Delta x_t = (1 - L)x_t = C(L) \; \epsilon_t \tag{2}$$

Using the multivariate Beveridge-Nelson decomposition, the matrix polynomial can be written as

$$C(L) = C(1) + (1 - L)C^*(L) \tag{3}$$

where $C^*(L)$ is a matrix in the lag operator with $A_j^* = -\sum_{k=j+1}^{\infty} A_k$. We can then write the vector moving average (VMA) process in equation (2) as

$$\Delta x_t = C(1)\epsilon_t + (1 - L)C^*(L)\epsilon_t \tag{4}$$

Suppose now that there is a vector α such that $\alpha' C(1) = 0$, cancelling the difference operator on both sides, equation (4) will then reduce to

$$\alpha' x_t = \alpha' C^*(L)\epsilon_t \tag{5}$$

where the right-hand side is a vector moving average process that is always stationary. Premultiplying the original time series vector x_t, which is $I(1)$, with the vector α' will result in a stationary process with $\alpha' x_t) \sim I(0)$. The vector α is refered to as the cointegrating vector. The crucial condition for cointegration is therefore that $\alpha' C(1) = 0$. Furthermore, any linear combination of α is also a cointegrating vector as $\lambda \alpha' C(1) = 0$ for any $\lambda \neq 0$. (Hamilton, 1992)

Following Engle and Granger (1987), we can then define cointegration formally as:

> The components of the vector x_t are said to *be cointegrated of order* d, b, denoted $x_t\ CI(d, b)$ if (i) all components are $I(d)$; (ii) there exists a vector $\alpha \neq 0$ so that $z_t = \alpha' x_t \sim I(d - b), b > 0$. The vector α is called *cointegrating vector.*

For most economic questions, the order of cointegration will be one, so that the series itself is not stationary, but the differences Δx_t are. $\alpha' x_t$ can be interpreted as the equilibrium error. This suggests that any deviation from the long-run relationship will be transistent only and does not have a steady impact. (Watson, 1994).

3.2 Error Correction Model

The results of the previous section gives way to different representations of the cointegrated process. Let y_t be a $(k \times 1)$ vector of integrated time series and suppose the data generating process follows a VAR$(p-1)$ with

$$y_t = \mu + \delta t + \sum_{s=1}^{p-1} A_s y_{t-s} + \epsilon_t \tag{6}$$

where μ is a constant, β the coefficient on the deterministic time trend t and the A_s sequence represents $(p-1)$ $(k \times k)$ matrices.

The Granger representation theorem states that if a set of $I(1)$ variables is cointegrated, they have the following Vector Error Correction representation:

$$\Delta y_t = \mu + \delta t + \Pi y_{t-1} + \sum_{s=1}^{p} \Gamma_s \Delta y_{t-s} + \epsilon_t \tag{7}$$

where $\Pi = -(I_k - A_1 - A_2 - \cdots - A_p)$ and $\Gamma_i = -(A_{i+1} + A_{i+2} \cdots + A_p)$ for $i = 1, 2, \cdots, p$

The VECM representation is essentially a VAR in differences with the short-term parameters Γ and the additional term Πy_{t-1}, where Π is a $(k \times k)$ matrix. This restriction on the differenced VAR ties the individual series of the vector y_t together and ensures that the system returns to its long run equilibrium. (Banerjee et al., 1993).

The matrix Π and its rank $r = rk(\Pi)$ are of crucial importance for the cointegration relationship of the system. If Π has rank of zero, the term drops out. In this case, all the individual series are unit root processes and equation (7) therefore reduces to a stable VAR in differences with no cointegration relationship. (Enders, 1995)

If Π has full rank, all series in the system are stationary and therefore each linear combination will be stationary as well. This scenario is called trivial cointegration as cointegration is formally present, but the individual series do not share a common stochastic trend.

The interesting case is when Π has a rank between 0 and k. If Π is rank deficient, it can be written as $\Pi = \gamma\alpha'$ where γ and α are $(k \times r)$ matrices. There are r linearly independent cointegrating relationships in the system. The matrix α, called the cointegrating matrix, collects all the linearly independent cointegrating vectors.

The parameter γ, also called the loading, feedback or adjustment matrix, can be interpreted as the speed of adjustment to errors in the long-run relationship. If the system is out of equilibrium, that is if $\alpha y_t \neq 0$, the loading matrix controls the change Δy_t in the next period to drive the time series back to the relationship given by the cointegrating matrix. Bigger values in γ correspond to faster adjustment to the long-run equilibrium. The matrices γ and α are not unique and can be decomposed arbitrarily.[2] A feasible way is therefore to normalize the first component of the cointegration vector to one. (Luetkepohl, 2005)

The parameter sequence Γ measures short-term reactions of a series to changes in its own past values as well as those in other variables in the system just like in the standard non-cointegrated VAR. As the differences are stationary, the effect of these short-term fluctuations eventually die out and do not have an influence to the long-run relationship.

Estimation of the VECM can be done by standard OLS or using the Maximum Likelihood approach. Engle and Granger (1987) proposed a two-stage method which at first estimates the cointegrating vector α by regressing one time series in the system on the remaining variables. In a second step, the estimated cointegration vector is used to estimate equation (7). The Maximum Likelihood method developed by Johansen (1988) is a full information approach that estimates the VECM in a single step. This procedure has the advantage that it does not carry over estimation errors of the first step into a second one and therefore yields more efficient estimators. (Maysami and Koh, 2000).

[2]For example, define $\gamma^* = \gamma Q'$ and $\alpha^* = \alpha Q$, then $\gamma^*\alpha^* = \gamma\alpha$.

3.3 Testing for a Unit Root

One basic requirement for the presence of cointegration is that all the time series are integrated of the same order. Therefore the researcher needs tests to figure out whether the series are stationary. In the economic practice, two tests have been widely used to determine the order of integration: The Augmented Dickey Fuller Test developed by Dickey and Fuller (1979) as well as the Phillips-Perron test (Phillips and Perron, 1988).

The Augmented Dickey Fuller (ADF) test allows to test for a unit root in the presence of autocorrelation in the error terms. The idea is to approximate the ARMA structure of the residuals by adding own lags of the process to the test regression to achieve i.i.d. errors. Consider the following setup

$$y_t = \mu + \beta t + \phi y_{t-1} + u_t \tag{8}$$

with μ being a constant, t a trend and the error term u_t being given by the stationary ARMA(p,q) process

$$u_t = \sum_{i=1}^{p} \phi_i u_{t-i} + \sum_{i=1}^{q} \theta_i \epsilon_{t-i} + \epsilon_t \tag{9}$$

where ϕ_i are the AR and θ_i the MA coefficients respectively. The idiosyncratic error ϵ_t is supposed to follow an i.i.d. sequence. If u_t is stationary and invertible, it can be written as the AR(∞) process

$$u_t = \sum_{i=1}^{\infty} d_i u_{t-i} + \epsilon_t \tag{10}$$

where d_i is the sequence of the resulting AR coefficients. Now assume that this process can be approximated by an AR(k) process

$$u_t = \sum_{i=1}^{k} d_i u_{t-i} + e_t \tag{11}$$

where e_t captures the idiosyncratic error ϵ_t and the error resulting by the approximation.

Under the null that there is a unit root, the differences of the process y_t are simply given by the correlated errors such that $\Delta y_t = u_t$. Using this approximation for u_t, equation (8) can be written as

$$y_t = \mu + \phi y_{t-1} + \sum_{i=1}^{k} \phi_i \Delta y_{t-i} + \epsilon_t \tag{12}$$

and after subtracting y_{t-1}

$$\Delta y_t = \mu + \gamma y_{t-1} + \sum_{i=1}^{k} \phi_i \Delta y_{t-i} + \epsilon_t \tag{13}$$

where $\gamma = (\phi - 1)$. Estimating equation (13) by standard OLS allows us to test the null hypothesis of y_t containing a unit root, $H_0 : \gamma = 0$, against the alternative that the process is stationary, that is $H_1 : \gamma < 0$.[3] However, under the null the t_{ADF} statistic has a non-normal distribution, even in the limit. Critical values can therefore be found in Dickey and Fuller (1979).

The ADF test provides a simple testing procedure, but also comes with some severe drawbacks. Choosing the lag length to approximate the autocorrelation structure is a sensitive issue. If the lag length is chosen to be too small, the test will be biased as the errors are not i.i.d. However, if k is too large, more parameters have to be estimated and the test will suffer from a loss of power. (Schwert, 1989).

For the empirical practice, various procedures to determine the appropriate lag length have been suggested in the literature. Ng and Perron (1995) suggested a step-wise data-based lag selection procedure to choose the number of lags. At first, a maximum lag length k_{max} is chosen and equation (13) estimated by standard OLS. If the coefficient on the longest lag is significant, the specification with $k = k_{max}$ is accepted. If not, k is reduced by one and equation (13) estimated again. The testing procedure is repeated until the last lag is

[3] The case of explosive processes with $\phi \geq 1$ is not considered here.

significantly different from zereo. Again, the problem with this down testing procedure is the choice of k_{max} where the researcher has to rely on a priori knowledge or economic theory.

Another popular unit root test is the Phillips-Perron (PP) test (Phillips and Perron, 1988). The PP test differs from the ADF test mainly in how it deals with autocorrelated and heteroskedastic error terms. While the ADF regression approximates the ARMA structure of the errors with a parametric autoregression, the PP test directly modifies the test statistic. The test considers following regression where any autocorrelation in the errors has been ignored:

$$\Delta y_t = \mu + \beta t + \alpha y_{t-1} + u_t \tag{14}$$

with μ being a constant and u_t the stationary error term that may be autocorrelated and homoskedastic. The null hypothesis $H_0 : \alpha = 0$ is the same as for the ADF test. However, instead of evaluating the statistic t_α directly the Phillips-Perron test uses the transformation

$$Z(t_\alpha) = \frac{\tilde{\sigma}^2}{\tilde{\lambda}^2}\, t_\alpha - \frac{1}{2}\left(\frac{\tilde{\lambda}^2 - \tilde{\sigma}^2}{\tilde{\lambda}^2}\right)\left(\frac{T \cdot SE(\tilde{\alpha})}{\tilde{\sigma}^2}\right) \tag{15}$$

where $\tilde{\sigma}^2$ is the consistent estimate of the error variance σ_2 using the OLS residuals $\tilde{u}_t$ with

$$\tilde{\sigma}^2 = \lim_{T\to\infty} T^{-1} \sum_{t=1}^{T} E[\tilde{u}_t^2] \tag{16}$$

and $\tilde{\lambda}^2$ is the Newey-West estimator estimator of the long-run variance:

$$\tilde{\lambda}^2 = \lim_{T\to\infty} \sum_{t=1}^{T} E\left[T^{-1} \sum_{t=1}^{T} \tilde{u}_t\right] \tag{17}$$

These parameters guide the correction for autocorrelation and heteroskedasticity.

Phillips and Perron (1988) showed that if the null hypothesis is true, the ADF and PP tests have the same distribution and therefore use the same critical values of Dickey and Fuller (1979). Although both tests are asymptotically equivalent, in small samples the differences might be considerable. In economic practice, the PP test is often prefered as its non-parametric approach to modelling the nuisance parameters allows application to a wide range of time-series processes including weakly dependent and heterogeneously distributed data.

3.4 Testing for a Cointegration vector

Engle and Granger (1987) propose a simple three-step procedure to test for cointegration. Assume that x_t and y_t are two unit root processes that are integrated of order one. Engle and Granger suggest to simply estimate the cointegration regression by standard OLS:

$$y_t = \tilde{\alpha} + \tilde{\beta} x_t + \tilde{u}_t \tag{18}$$

Stock and Watson (1987) show that if cointegration is present, the OLS estimators are consistent even if x is correlated with the error term and converge to the true value at a the faster rate T compared to the usual $T^{1/2}$ rate.[4]

In a second step, the estimated errors $\tilde{u}_t$ are obtained by subtracting the fitted values from the actual ones

$$\tilde{u}_t = y_t - \tilde{\alpha} - \tilde{\beta} x_t \tag{19}$$

and test them for stationarity using the standard Dickey-Fuller test. This procedure is called the Cointegration Regression Dickey-Fuller (CRDF) test. If the errors are believed to be autocorrated, using the ADF is more appropriate and this procedure is subsequently called the Cointegration Regression Augmented Dickey-Fuller (CRADF) test. In the same fashion as in the preceding section, the autocorrelation is being corrected for by including lags into the test equation.

[4] See the proof for consistency in the Appendix.

$$\Delta\tilde{u}_t = \mu + \beta t + \gamma\tilde{u}_t + \sum_{j=1}^{k} \Delta\tilde{u}_{t-j} + \epsilon_t \tag{20}$$

If $H_0 : \gamma = 0$ can be rejected, we will conclude that the linear combination of the both time series is stationary and that there is cointegration present in the system. If H_0 cannot be rejected, we will assume that the series $\tilde{u}_t$ contains a unit root and accept H_1 that there is no cointegration.

If there are more than two time series in the cointegrating regression, there may be more than one cointegrating vector. If this is the case, it is not clear what the standard OLS method is estimating in equation (18). Are more appropriate method for testing cointegration in a multivariate setting has been developed by Johansen (1988, 1991). Johansen derives the maximum likelihood estimator of the cointegration space. Test is based on the likelihood ratio (LR) test of the hypothesis that the cointegration space is restricted to lie in a certain subspace.

The Johansen procedure relies on certain assumptions which are (Burke and Hunter, 2005, 106):

1. The data generating process for the VAR in equation (21) is correctly specified.
2. The errors are i.i.d. Gaussian random variables with mean zero and variance-covariance matrix Λ.
3. There are no structural breaks.
4. All the series in the system are integrated of the same order.

The Johansen test relies on the VAR process

$$x_t = \Pi_1 x_{t-1} + \cdots + \Pi_k x_{t-k} + \epsilon_t \tag{21}$$

where ϵ_t is a $p \times k$ vector and follows the distribution $\epsilon_t \sim N(0, \Lambda)$. Writing the vector autoregression as a error correction model like in equation (7)

$$\Delta X_t = \Gamma_1 \Delta x_{t-1} + \cdots ... + \Gamma_{k-1} \Delta x_{t-k+1} + \Gamma_k x_{t-k} + \epsilon_t \tag{22}$$

where again $\Gamma_i = -I_k + \Pi_1 + \cdots + \Pi_i, \quad i = 1, \cdots, k..$ and $\Pi = \gamma\alpha'$ with α being the cointegrating vector. To test for the cointegration rank, Johansen proposes two different pairs of hypothesis, which are

$$H_0 : rank(\Pi) = r \quad against \quad H_1 : r < rank(\Pi) \leq K \tag{23}$$

$$H_0 : rank(\Pi) = r \quad against \quad H_1 : rank(\Pi) = r + 1 \tag{24}$$

Johansen showed that the test statistics $\lambda_{trace}(r, K)$ to test (23), referrred to as the trace statistic, and $\lambda_{max}(r, r+1)$ for testing (24), known as the maximum eigenvalue statistic, are asymptotically distributed as

$$\lambda_{trace}(r, K) \xrightarrow{d} tr(D) \tag{25}$$

$$\lambda_{max}(r, r+1) \xrightarrow{d} \lambda_{max}(D) \tag{26}$$

where tr is the trace operator and $\lambda_{max}(D)$ is the maximum eigenvalue of the matrix

$$D := \left(\int_0^1 W dW' \right)' \left(\int_0^1 W W' ds \right)^{-1} \left(\int_0^1 W dW' \right) \tag{27}$$

with $W = W_{K-r}(s)$ being a $(K-r)$-dimensional standard Wiener process.

To determine the cointegration rank, Johansen proposes a sequential testing procedure starting to test the null of $H_{0,0} : rank(\Pi) = 0$ against the alternatives given in (23) and (24). If the null can be rejected, the sequence proceeds to test the new null hypothesis $H_{0,1} : rank(\Pi) \leq 1$, continuing with $H_{0,j} : rank(\Pi) \leq j$ against the alternatives until the null cannot be rejected for the first time. The cointegration rank is then chosen as $r = j$.

The Johansen testing procedure is sensitive to the lag length which can be selected by using information criteria. As the Johansen procedure rests on the assumptions that the residuals are i.i.d., one requires tests to ensure the appropriate behavior of the error term. Asymptotally, the trace and maximum eigenvalue are equivilent. In small samples however, the two tests can give different results and lead to incorrect inference.

3.5 Impulse Response Functions

When dealing with stock market cointegration, it is of special interest to know how one market responds to innovations in the others in a complex system. For dealing with dynamic systems, impulse response analysis has now become a common tool. Impulse response functions allow to trace out the effect of an exogenous shock, or an impulse, in one variable to the system over time. This is a single shock of one unit of its standard deviation in t with all errors in other periods set to zero. (Koop et al., 1996)

For stationary VARs, obtaining the impulse response functions is comparatively easy. If the k-dimensional VAR(p) with coeffients $\{A_i\}_{i=0}^{p}$ is stable, it can be rewritten as an infinite vector moving average process:

$$x_t = \mu + \sum_{i=0}^{\infty} \Phi_i u_{t-i} \tag{28}$$

where Φ_0 is the identity matrix I_k and other coeffients can be computed recursively as $\Phi_i = \sum_{j=1}^{i} \Phi_{i-j} A_j$. The MA coefficient matrices Φ_i contain the impulse responses of the system with the jth column of indicating the responses of each variable to a unit shock to the jth variable in the system. (Luetkepohl, 2005). The sequence Φ_i then traces the time path of a shock over time.

The impulse response function pictures the effect of an idiosyncratic error in one variable to the other variables in the system. However, in real world applications the errors in a system of equations are unlikely to be independent of each other, but rather contemporaneously correlated, that is if the variance covariance matrix Ω is not diagonal. One way to obtain isolated errors is to use the Cholesky decomposition of the covariance matrix.

$$\Omega = ADA' \tag{29}$$

where A is a lower triangular and D a diagonal matrix. The orthogonalized shocks ϵ_t can then be calculated by $\epsilon_t = A^{-1}u_t$ and used for the impulse response analysis as they are not correlated anymore.

$$\begin{aligned} E(\epsilon_t \epsilon_t') &= A^{-1} E(u_t u_t') \left(A^{-1}\right)' \\ &= A^{-1} \Omega \left(A^{-1}\right)' \\ &= A^{-1} A D A' \left(A^{-1}\right)' \\ &= D \end{aligned} \tag{30}$$

In stable systems, the MA coeffients Φ_i go to zero and the impulse responses will die out as $t \to \infty$. However, a non-stationary VAR does not have a valid VMA representation as in equation (28) as the MA coefficients do not converge to zero. This means that a exogenous shock to one variable in the system can have persistent effects. (Luetkepohl and Reimers, 1992)

When cointegration is present, there are two general ways to estimate impulse response functions which differ in the way they incorporate the cointegrating vector. The easiest way is simply to write the model as a VAR in levels and to ignore the long-term relationship restrictions of the cointegrating vector. The advantage of this method is that vector autoregressive systems are much easier to estimate than the VECM. The VAR coefficients are consistent and converge at a faster rate when cointegration is present, though are not efficient as they do not incorporate the information provided in the cointegrating vector. (Mitchell, 2000 and Phillips, 1998).

Using Monte Carlo simulations, Naka and Tufte (1997) have shown that impulse response functions estimated from the VAR perform well at short horizons and are nearly identical to the results obtained from the VECM. At longer horizons however they diverge from the true value as the VAR is not able to catch the persistent effect. Mitchell (2000) in contrast provides evidence that the bias can be evident in both short and long-run horizon. Though the VAR coefficients are consistent, it does not follow that the IRFs are consistent as well. He argues that even in large samples, this is a considerable problem and estimated IRFs from the levels VAR tend to go to random variables, not to the true value. Therefore, estimating the cointegrating vector may still be better than ignoring the long-run relationship.

To obtain the impulse response functions for a cointegrated system, Naka and Tufte (1997) propose a step-wise method based on the vector error correction model:

1. Determine the cointegration rank with Johansen's (1988) method and estimate the cointegrating vector.
2. Estimate the vector error correction model in (7) using the cointegrating vector obtained in step one.
3. Transform the VECM into a VAR in levels using the relationship $\Pi = -(I_k - A_1 - A_2 - \cdots - A_p)$.
4. Obtain the impulse response function from the moving average representation of the levels VAR.

The drawback of this method is that it relies on a point estimate of the cointegrating vector or vectors. In finite samples, point estimates in general lack power and incorporating this constraint into the VECM may further reduce validity of the inference drawn from the impulse response functions. Naka and Tufte (1997) have shown that IRFs estimated from the vector error correction perform poorly compared to ones obtained from an unrestricted VAR. Furthermore, this method lacks implementation in econometric software and to my knowledge, only the JMulti package provided by Luetkepohl and Kraetzig (2004) supports the estimation of impulse responses from the VECM.

3.6 Regime Change

All the presented methods rely on the assumption that the parameters of the data generating process are constant and do not allow for a regime change. To account for a structural break, Gregory and Hansen (1996) developed a cointegration test that models a regime change in the cointegration vector.

Let the observed data be $y_t = (y_{1t}, y_{2t})$ with y_{2t} being a $(m \times 1)$ vector of variables integrated of order one. Then the standard cointegrating regression is given by

$$y_{1t} = \mu + \alpha' y_{2t} + e_t \quad t = 1, \cdots, n \tag{31}$$

with n being the sample size and the error term $e_t \sim I(0)$. In the classical cointegration setup, the parameters μ and α are considered to be time-invariant. In practice however, structural changes in the cointegrating relationship may be possible. In this case, the standard ADF and Phillips-Perron might lead to misleading conclusion if one does not take into account changing parameters in the cointegrating regression. Gregory et al. (1996) showed that the ADF test has low power if a structural break is present.

To model the structural break, Gregory and Hansen (1996) define the dummy variable ϕ_τ to account for the regime shift:

$$\phi_\tau = \begin{cases} 0, & \text{if } t \leq [n\tau] \\ 1, & \text{if } t > [n\tau] \end{cases} \tag{32}$$

where $\tau \in (0, 1)$ is the unknown relative timing of the structural break, n the sample size and [ ] denotes the integer part of a real number.

Gregory and Hansen develop tests for three different types of structural breaks. The simplest specification is a change in the intercept, while the slope coefficient α remains constant. This indicates a parallel shift in the long-run equilibrium and is referred to as level shift:

$$y_{1t} = \mu_1 + \mu_2\phi_\tau + \alpha' y_{2t} + e_t \tag{33}$$

with μ_1 being the intercept before the shift and $\mu_1 + \mu_2$ the one thereafter. This specification can easily be extended with a deterministic time trend βt and called level shift with trend:

$$y_{1t} = \mu_1 + \mu_2\phi_\tau + \beta t + \alpha' y_{2t} + e_t \tag{34}$$

The most flexible specification of the structural break incorporates a change in both the intercept and the slope coefficients. This allows the long-run equilibrium to shift parallel and to rotate as well. This model is referred to as the regime shift model with α_1 being the slope before and $\alpha_1 + \alpha_2$ the slope after the structural break respectively:

$$y_{1t} = \mu + \mu_2\phi_\tau + \alpha_1' y_{2t} + \alpha_2' y_{2t}\phi_\tau + e_t \tag{35}$$

Gregory and Hansen provide a residual-based procedure to test the null of no cointegration against the alternative models in equations (33-35). If a structural break is present, the ADF and Phillips-Perron statistics under the null do not have the same distribution as in a time-invariant model and can lead to incorrect inference. In specific, the ADF fails to reject the null of non-stationarity too often if the parameters change.

The Gregory and Hansen test proceeds as follows. Firstly, as the break point is seldom known a priori, the assumed cointegrationg regression of (33-35) is estimated by standard OLS for each possible feasible break points $\tau \in T$. From the regressions, the series $\tilde{e}_{t\tau}$, now being a function of τ, is obtained and the test statistic is computed for all possible values in the set. In principle the set T could contain all observations, but in practice it has to be restricted to allow the test statistic to be computed. Gregory and Hansen suggest to restrict the set to $[0.15, 0.85]$ which specifies the center 70% of the sample to be possible break points.

The ADF statistic is the same as in equation (13) and obtained by regressing the differences of $\tilde{e}_{t,\tau}$ on the past level value and a suitable number of lagged differences to account for autocorrelation.

$$\Delta\tilde{e}_{t,\tau} = \gamma\tilde{e}_{t-1,\tau} + \sum_{i=1}^{k} d_i \Delta\tilde{e}_{t-i,\tau} + u_t \tag{36}$$

The ADF(τ) statistic is then the t-statistic of γ.

The Phillips-Perron statistic $Z_t(\tau)$ is computed as follows. At first estimate the first-order autocorrelation $\tilde{\rho}_\tau$ of the residuals

$$\tilde{\rho}_\tau = \sum_{t=1}^{n-1} \tilde{e}_{t,\tau}\tilde{e}_{t+1,\tau} \left(\sum_{t=1}^{n-1} \tilde{e}_{t,\tau^2}\right)^{-1} \tag{37}$$

Using the correlation coefficient we can form the bias-corrected version of the errors

$$\tilde{\nu}_{1,\tau} = \tilde{e}_{t,\tau} - \rho_t\tilde{e}_{t-1,\tau} \tag{38}$$

and form the Phillips-Perron Z_t statistic

$$Z_t(\tau) = (\tilde{\rho}^*_\tau - 1)/\tilde{s}_\tau, \qquad \tilde{s}_\tau = \tilde{\sigma}^2_t / \sum_{1}^{n-1} \tilde{e}^2_{t,\tau} \tag{39}$$

To test the null of cointegration in presence of a structural break agains the alternative that equation (31) is the correct specification, Gregory and Hansen consider the smallest value of the statistics, denoted by the infimum operator inf().

$$Z_t^* = \inf_{\tau \in T} Z_t(\tau) \tag{40}$$

$$ADF^* = \inf_{\tau \in T} ADF\,(\tau) \tag{41}$$

The minimum value will indicate the most likely timing for the structural break. The authors use simulation methods based on MacKinnon (1996) to provide critical values for the three different test statistics and the three model specifications for up to four regressors.

4 Data

4.1 Data Sampling

I use weekly closing price for the indices of eight Asian stock markets and the US market. These are the American Standard & Poor's 500 index, the Japanese Nikkei 225, Hong Kong's Hang Seng index, the South Korean KOSPI 200, the FTSE Thailand index, Singapore's EPRA/NAREIT, Bursa Malaysia's KLCI, the Taiwanese Weighted Index, and the PSI index of the Phillipines. The sample period runs from January 1995 to August 2010. This corresponds to 817 observations for all the nine stock markets in the system. All data for the indices has been sampled from Reuter's Datastream platform. The natural logarith is applied to all the stock price indices. This allows to specify the relationship in percentage form and has the further advantage that the differences can be directly interpreted as returns.

The data has been sampled for weekly data for specific reasons. In general, the frequency of the data is an important question for analysing stock market cointegration as it implicitly imposes a-priori restrictions on the adjustment processes. With electronic trading platforms and financial services such as Datastream, nowadays stock price data can be sampled in almost real time. With ultra-high frequency, the sample size grows rapidly which might seem preferable from an econometrician's view. Though automated trading has been advanced in the recent past, most trading is still done by humans who simply need a certain positive amount of time to process ninformation and include it into their investment strategy. At too high frequencies, time intervals may become arbitrary and random as trading activities cannot be assigned to a specific time anymore. The choice of frequency therefore always involves a trade-off between sample size and economic plausability.

Previous studies have used different approaches and in general three different frequencies have become common in the literature: daily, weekly, and monthly data. Any smaller units than daily intervals would lead to a model of intra-day trading rather than the modelling of long-run stock market relationships and have therefore been rejected. Any lower frequency than monthly data may strongly focus on long-run equilibria and still be valid for modelling stock market linkages. Yet annual or semi-annual data would ignore interesting patterns of short-run adjustment and also lower the sample size considerably. Econometric analysis may therefore not be valid if the frequency is too low.

From the three common sample frequencies, weekly data seems to be a feasible compromise between sample size and economic plausability. Weekly data clearly abstracts from any intra-day trading patterns such as the "lunch effect", which may be present in daily samples.[5] It also reduces but not entirely avoids the effect generated by the different trading times. The nine countries lie in four different time zones and trading times of the markets also differ. Compared to monthly data, weekly frequency has the advantage of leaving about four times as much observations for econometric analysis. It also allows for the investigation of short-run linkages between international stock markets and as I consider a week's time long enough for investors to process new information, I regard it as best suited for studying market linkages.

Another issue is the denomination of the stock index prices. In principle, the options are to use local currencies or to represent them in a common unit, such as on the basis of US dollar exchange rates. While most studies use local currencies, Masih and Masih (2001) employ dollar based data. Cointegration under the latter would imply that long-run equilibria between stock markets take into account international purchasing power, while a cointegration relationship in local currencies would suggest that exchange rates matter less. Bessler and Yang (2003) showed that the currency issue can significantly change the cointegration results. Therefore, to avoid any predetermination and to assess the influence of exchange rate fluctuations I follow Hung and Cheung (1995) and Yang et al. (2003) and collect data in both forms. Local currencies shall be the base case and later I will control the results for US dollar denominated data.

[5] Analysing Asian stock markets, this may be a considerable issue.

4.2 Descriptive Statistics for Stock Indices

The majority of stock markets performed well over the sample period. The US, Hong Kong and Korea stock price indices more than double their initial values, while the Malaysian, Taiwanese and Phillipenian markets still experience an overall positive growth. In contrast, the markets of Japan, Thailand and Singapore make severe losses. Over the roughly 15 years in the sample, the FTSE Thailand index loses 40%, the Nikkei even more than half of its value in January 1995. Furthermore, the volatility differs greatly among the nine stock markets in the sample. While the US market grows rather steadily, the Asian markets, and especially the Southeast Asian ones, are much more volatile. With a standard deviation of 5.5 percentage points and changes of up to 29% in a single week, the Thai market is the most unsteady one.

Changing the denomination of the indices to a common representation in US dollar, the major trends remain mainly unchanged. Yet it becomes obvious that changes in the exchange rates dampen the overall positive performance of the NIC stock markets. In general, South and East Asian currencies devalued against the US dollar in the sample period. If the Taiwan and Phillipines indices are expressed in dollar, the overall performance becomes negative. In contrast, the huge losses of the Nikkei become less severe as the Japanese Yen became stronger compared to the American currency. Table 1 summarizes the results in both local currency and US dollar denomination.

Visual analysis of the index charts reveals that the different markets show similar patterns as the markets share longer periods of steady growth or decline. These patterns are strongly linked to the international financial crises happening during the sample period: the Asian crisis of 1997/98, the dotcom bubble of 2001 and the downturn due to the subprime crisis of 2007. In contrast, the years 1999-2000, 2003-2007 and the recent recovery of 2009 can be viewed as global boom times. Yet the different markets do not react uniformly to the major trends. The US market for example seems to be virtually unaffected by the Asian financial

Figure 1: Index in percent for local and dollar denomination

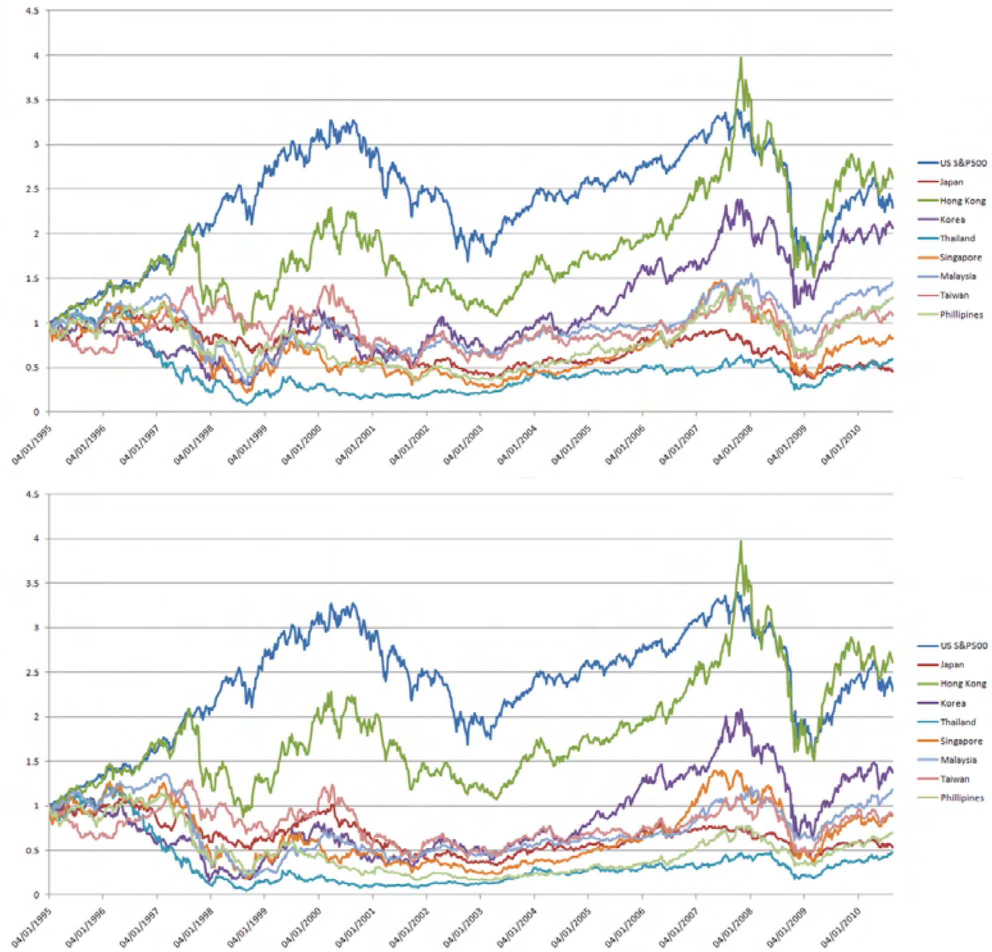


Table 1: Mean and standard deviation of stock index data

	Local currency			Dollar denomination		
	Weekly	**Volatility**	**Yearly**	**Weekly**	**Volatility**	**Yearly**
US S&P 500	0.10%	2.47%	6.21%	0.10%	2.47%	6.21%
Japan	-0.10%	3.14%	-3.96%	-0.08%	3.20%	-3.96%
Hong Kong	0.12%	3.58%	7.21%	0.12%	3.59%	7.21%
Korea	0.09%	4.45%	4.92%	0.04%	5.57%	4.92%
Thailand	-0.06%	5.51%	-4.33%	-0.09%	6.01%	-4.33%
Singapore	-0.02%	4.98%	-1.07%	-0.01%	5.24%	-1.07%
Malaysia	0.05%	3.34%	2.02%	0.02%	4.18%	2.02%
Taiwan	0.01%	3.59%	1.06%	-0.01%	3.89%	1.06%
Phillipines	0.03%	3.59%	0.62%	-0.04%	4.30%	0.62%

Weekly mean and standard deviation in percentage returns. Yearly return calculated as geometric average on the basis January 1995 - January 2010.

crisis of 1997, while most Asian indices lose heavily during this period. Correlation between weekly returns can be found in Table 10 in the Appendix.

5 Empirical Results

All estimation has been performed using the matrix-based environment Mathworks Matlab 7.10 and the open source software JMulti 4.24. The Econometrics toolbox and the Spatial Econometrics package for Matlab (LeSage, 1999) were of great use in estimating and testing the time series models. All programming codes are supplied electronically.

5.1 Unit Root Tests

Before any cointegration analysis can be done, one has to assure that all the stock index series are non-stationary and integrated of the same order. Performing the Augmented Dickey-Fuller with a constant and a time trend, the null hypothesis of a unit root cannot be rejected for the individual logged stock indices at the 95% level. The lag length k for the ADF test has been selected by the Ng and Perron (1995) downtesting procedure starting with a maximum lag of 12, which corresponds to a time span of about three months. However, the results of the ADF test are not sensitive to the choice of k and the null cannot be rejected for any number of lagged terms in each of the series. The Phillips-Perron test for non-stationary specified with a constant and deterministic trend confirms the results of the ADF test which clearly hints that all the stock indices series contain a unit root.

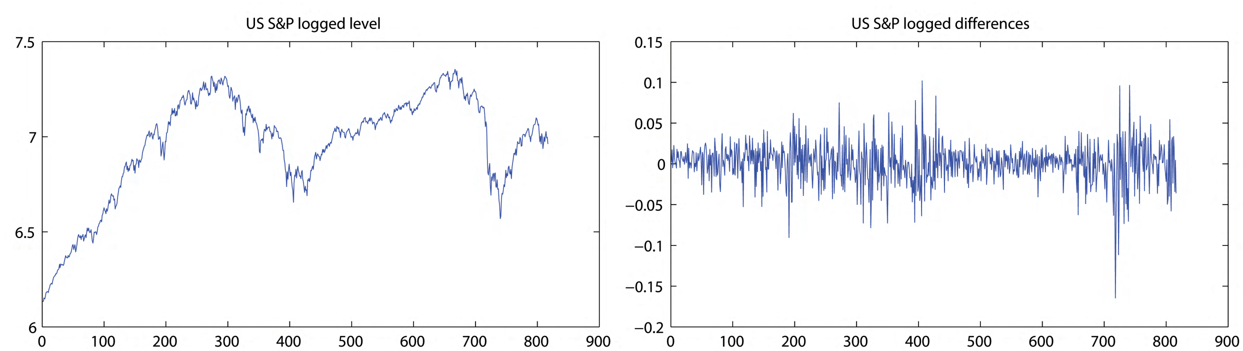


Figure 2: Levels vs differences

In a second step, I apply differences of the time series and compute the ADF and PP test statistic on the differenced data. This time, the null of non-stationarity is rejected for all indices at the 99% level. This suggests that weekly returns follow a stationary process. Since the original series must be differenced one time in order to achieve stationarity, I conclude that the stock market indices are integrated of order one, such that the (9×1) vector $x_t \sim I(1)$. The results of the tests are summarized in Table 2.

Table 2: Stationarity test results

	Levels			**First differences**		
	Lags	ADF	$Z(t_\alpha)$	Lags	ADF	$Z(t_\alpha)$
US S&P500	7	-2.26	-2.33	6	-11.46***	-30.13***
Japan	3	-2.01	-1.97	12	-7.86***	-29.35***
Hong Kong	8	-2.88	-2.69	7	-9.31***	-28.11***
Korea	5	-2.84	-2.67	4	-10.93***	-29.31***
Thailand	11	-2.05	-1.96	10	-7.71***	-29.50***
Singapore	4	-1.88	-1.96	3	-14.06***	-27.35***
Malaysia	10	-2.39	-2.15	11	-8.00***	-27.74***
Taiwan	9	-2.91	-2.64	1	-19.28***	-27.87***
Phillipines	8	-1.60	-1.55	7	-9.03***	-28.32***
95% Critical value		-3.43	-3.42		-3.43	-3.42

Test statistics for the ADF and PP tests for the null hypothesis $H_0 : \alpha = 0$ in the model $\Delta y_t = \mu + \beta t + \phi y_t + \epsilon_t$. * denotes significance at the 90% level, ** denotes significance at the 95% level, *** denotes significance at the 99% level

5.2 Cointegration Tests

Having confirmed that all the series are integrated of the same order, this allows to set up the cointegrating regression and test for cointegration. I proceed to test for mutual long-run equilibria by performing bivariate Cointegration Regression Augmented Dickey Fuller tests with a constant and a deterministic trend. The lag length has again been be determined by downward testing. The ADF procedure allows to test for cointegration between two stock indices, but ignores potential indirect transmission channels which might run through third-party stock markets.

Applying the CRADF test to the stock index series, there is only one statistically significant cointegration relationship between Korea and Malaysia at the 90% level. (See Table 3.). As the stock index charts showed quite similar patterns between the markets, this result is rather surprising. Indeed, checking for robustness to the lag specification finds another cointegrating vector between Korea and Singapore at lower lags. Changing the specification of the CRADF test to exclude the time trend reveals even more long-run relationships: US - Taiwan, Hong Kong - Korea and Taiwan - Phillipines at the 95% level, as well as US - Korea, US - Malaysia, Hong Kong - Malaysia and Singapore - Phillipines at the 90% significance level.

In general, the results for the CRADF cointegration test do not suggest much evidence for a long-run relationship between the Asian stock markets as only three out of 36 possible mutual relationships show some form of cointegration at the 95% significance level. The inference taken from the CRADF test is further weakened as the results are not robust to changes in the specification of the test. The lack of clear evidence from the test might be due to the known weaknesses of the CRADF testing procedure. In a system with multiple time series, mutual testing is unable to detect stock market relationship which involve more than two indices. As the market with the strongest international interaction appears to be Korea with alone four cointegrating relationships, followed by the US with three, this might suggest that there is a more complex long-run structure present among the stock markets in the system.

I now turn to the test for stock market cointegration using the Johansen (1988) procedure. The Johansen procedure allows to test for the cointegration rank for the whole system and therefore can detect indirect channels of stock market linkages. Analysing the VAR representation, estimates of the constant are statistically significant while the time trend is not. The Akaike information criterion picks a lag length of three, while the Schwarz-Bayes criterion suggests to include only one past value. In econometric practise, the loss of power when including too many regressors may be preferred over biased estimates if the lag

Table 3: CRADF test results

	JP	**HK**	**KO**	**TH**	**SP**	**MA**	**TW**	**PH**
US S&P500	-2.11	-1.89	-2.20	-2.84	-2.27	-2.63	-2.30	-2.40
Japan		-3.24	-2.24	-1.98	-3.19	-2.16	-2.20	-2.37
Hong Kong			-2.97	-2.99	-3.08	-2.68	-3.29	-3.41
Korea				-2.67	-3.41	-3.66*	-2.53	-3.06
Thailand					-2.06	-2.47	-1.88	-2.10
Singapore						-2.65	-2.02	-3.18
Malaysia							-2.16	-2.40
Taiwan								-3.46

* denotes significance at the 90% level, ** denotes significance at the 95% level, *** denotes significance at the 99% level

structure is too short. Therefore the determistic trend is dropped in the Johansen procedure and the tests performed with three lags.

The results indicate that there is a significant cointegration relationship betweeen Asia's stock markets. Both the trace and maximum eigenvalue tests reject the null hypothesis $H_0 : r \leq 0$ of no cointegration vector in the system at the 99% and 95% confidence level respectively. This indicates that there is at least one cointegrating vector. Proceeding with the sequential testing, the trace statistic for $H_1 : r \leq 1$ suggests that there is more than one cointegrating relationship. However the eigenvalue test does not confirm this result at the 95% confidence level, yet is very close to the 95% critical value. As all other hypotheses of a higher cointegration rank cannot be rejected at a statistically significant level, I conclude that there is a maximum of two cointegrating relationships in the system of Asian stock markets. Results can be found in Table 4.

Again, the specification of the lag length is a sensitive issue for estimating and testing the cointegration vector. Including more lags up to the maximum of 12, both tests clearly reject the null of no cointegration at the 99% level and the eigenvalue test tends to find a second cointegrating vector for lagged values up to 10 periods. This might indicate that there is another long-run relationship that needs more time to adjust. However, it is known that the maximum eigenvalue statistic is more reliable in finite samples. For this reason and to keep the model parsimonious, only one cointegrating vector is used in the further analysis.

Table 4: Johansen test for cointegration

Trace Test		**Critical Values**		
H_0	λ_{trace}	**90%**	**95%**	**99%**
$r = 0$	224.32	190.87	197.38	210.04
$r \leq 1$	162.99	153.63	159.53	171.09
$r \leq 2$	110.86	120.37	125.62	135.98
$r \leq 3$	74.03	91.11	95.75	104.96
$r \leq 4$	46.75	65.82	69.82	77.82
$r \leq 5$	27.28	44.49	47.85	54.68
$r \leq 6$	16.42	27.07	29.80	35.46
$r \leq 7$	7.94	13.43	15.49	19.93
$r \leq 8$	0.08	2.71	3.84	6.63
Max Eigenvalue		**Critical Values**		
H_0	λ_{max}	**90%**	**95%**	**99%**
$r = 0$	61.33	55.24	58.43	65.00
$r \leq 1$	52.13	49.29	52.36	58.66
$r \leq 2$	36.83	43.29	46.23	52.31
$r \leq 3$	27.29	37.28	40.08	45.87
$r \leq 4$	19.47	31.24	33.88	39.37
$r \leq 5$	10.86	25.12	27.59	32.72
$r \leq 6$	8.47	18.89	21.13	25.87
$r \leq 7$	7.87	12.30	14.26	18.52
$r \leq 8$	0.08	2.71	3.84	6.63

5.3 VECM Results

Having found at least one statistically significant cointegrating vector, I proceed to estimating the Vector Error Correction Model with three lags and only one cointegrating vector ($r = 1$) based on the largest eigenvalue found by the Johansen cointegration test. This specification corresponds to the results from the maximum eigenvalue test who only found one significant cointegrating vector. For the estimation, the cointegrating vector has been normalized with respect to the US stock market as in Table 5.

Before any inference can be drawn for economic analysis, the specificiation of the model has to be checked for accuracy. The errors from the estimated model with $r = 1$ seem to be fairly normal, with the fat tails usually observed for financial return data. (Tsay, 2005) Figure 3 plots the standardized residuals of each of the nine regression equations with

Table 5: Estimated cointegrating vectors

	Estimate	**Normalized**
US S&P500	-6.217	1.000
Japan	1.222	-0.197
Hong Kong	7.114	-1.144
Korea	-0.872	0.140
Thailand	1.834	-0.295
Singapore	-0.019	0.003
Malaysia	-4.321	0.695
Taiwan	4.593	-0.739
Phillipines	-4.021	0.647

a standard normal distribution for comparison. However, the Jarque-Bera test rejects the null hypothesis that the data come from a normal distribution with a very low p-value of less than 0.01 for all nine equations. Performing the Ljung-Box Q-test for autocorrelation on the residuals with a maximum of 12 lags, the results indicate that most series are not correlated with past values. Only the error terms of the US and Korean stock market equation show signs of autocorrelation on a significant level. Furthermore, Engle's (1982) ARCH test confirms a heteroskedastic behavior as the null of homoskedasticity is rejected for all the nine residuals. Again, ARCH patterns are common for financial data and indicate times of low and high volatility. Asymptotically, the limiting distribution does not depend on normality and should not pose a problem. However, with the finite sample size in this analysis, all the inference relying on assumptions about the distribution of the error terms should be viewed with care.

The results of the simple model show that most of the coefficients of the loading matrix γ governing the adjustment to the long-run relationship are significantly distinct from zero. (See Table 7) With the exception of the US market, they all have the predicted negative sign, which indicates that the disequilibrium given in the error correction term αy_t will be reduced period by period. However, the size of the estimates differs widely and is quite small compared to the short-term adjustment parameters. These results suggest that distortions in the long-run equilibrium will be corrected slowly and unevenly among the nine stock markets.

Figure 3: Density of residuals

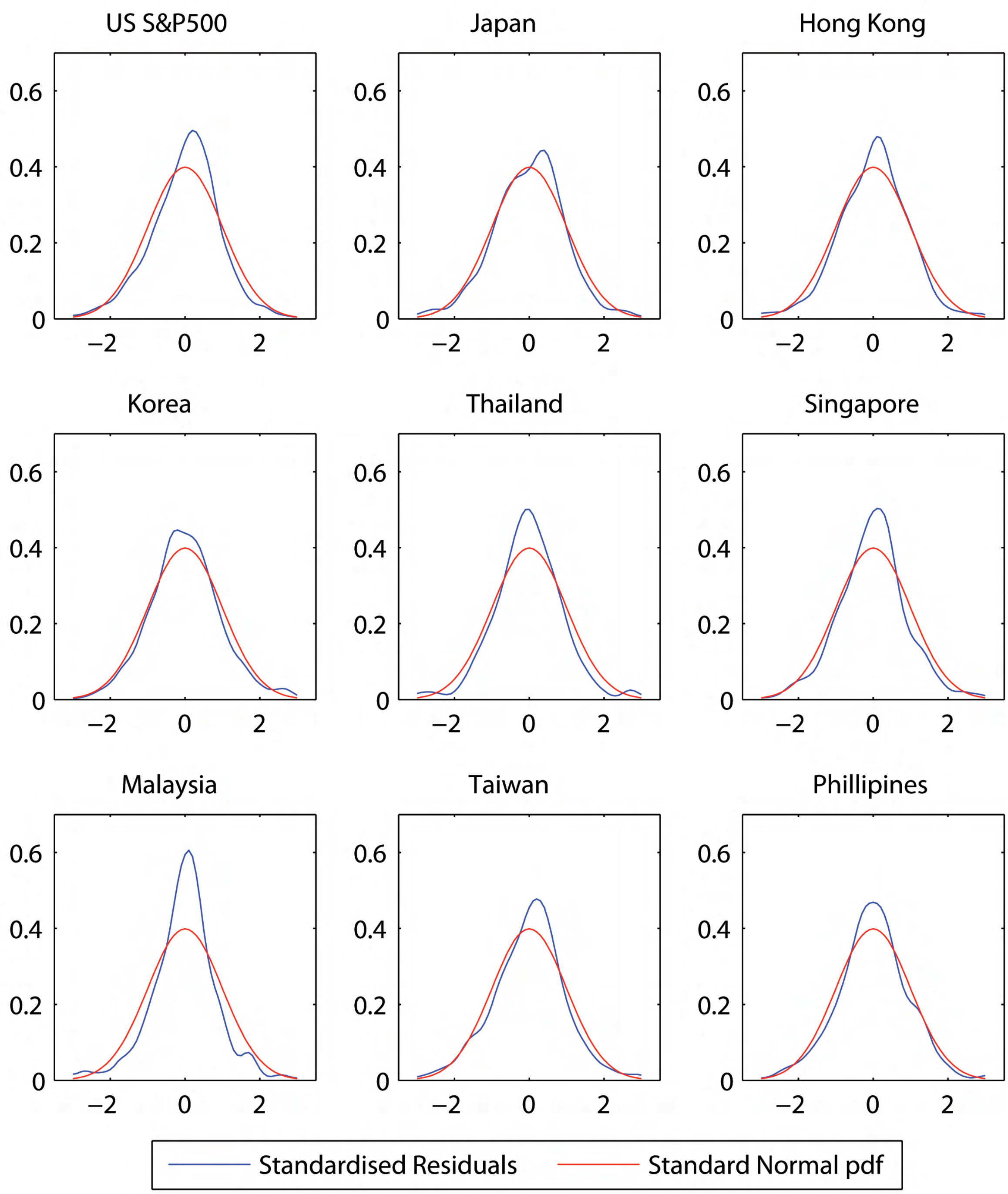


Table 6: Estimated residual density functions

	Ljung-Box	**ARCH**	**Jarque-Bera**
US S&P500	25.55**	19.49***	386.01***
Japan	14.87	2.79*	133.70***
Hong Kong	16.54	13.28***	440.27***
Korea	22.01**	72.32***	111.76***
Thailand	19.49	16.19***	592.41***
Singapore	17.05	49.47***	79.68***
Malaysia	18.57	44.68***	259.10***
Taiwan	9.47	13.25***	48.90***
Phillipines	15.31	9.02***	131.68***
95% Critical value	21.03	3.84	5.91

* denotes significance at the 90% level, ** denotes significance at the 95% level, *** denotes significance at the 99% level

The Korean KOSPI seems to return most quickly to the long-run cointegrating relationship, followed by the Taiwanese Weighted Index. The Thailand, Nikkei, Singapore and Hong Kong markets follow with similar values, while the, however statistically not significant, estimates for the markets of Malaysia and the Phillipines indicate that these markets hardly react to a disequilibrium at all. The S&P 500 index is the only one which does not tend to return to the long-run equilibrium as the coefficient on the error term is positive. The results of the VECM suggest that the US market is the leader in the system and that the Asian markets carry the burden of adjustment to return to the long-run relationship. The most integrated markets seem to be Korea and Taiwan, while it is unlikely that Malaysia and the Phillipines react much to distortions of the equilibrium. Table 7 reports the results.

The theory of the S&P 500 index being the leader is further bolstered by analysing the Granger causality tests presented in Table 8. The US stock market is Granger-causal for all the other stock markets in the system with the exception of Thailand and Malaysia. In contrast, past returns of the Nikkei 225 index do not help to forecast any other stock markets in the system, not even its own returns. This result indicates that although Japan is by far the biggest Asian economy in the analysis, its stock market does not have a big influence on the regional markets. However, it does not follow that the Japanese market is an isolated one, as the estimates suggest that the Nikkei 225 significantly reacts to changes in the stock

Table 7: Coefficients for loading matrix

Market	γ	t-stat
US S&P500	0.0018	2.16**
Japan	-0.0033	-3.10***
Hong Kong	-0.0030	-2.47**
Korea	-0.0068	-4.48***
Thailand	-0.0039	-2.07**
Singapore	-0.0033	-1.93*
Malaysia	-0.0007	-0.62
Taiwan	-0.0047	-3.81***
Phillipines	-0.0007	-0.61

* denotes significance at the 90% level, ** denotes significance at the 95% level, *** denotes significance at the 99% level

Table 8: Granger causality test results

	Granger caused by lagged values of								
Stock market	**US**	**JP**	**HK**	**KO**	**TH**	**SP**	**MA**	**TW**	**PH**
US SP500	1.13	0.33	2.58*	2.76**	0.73	2.15*	1.22	0.11	1.19
Japan	9.68***	1.98	3.07**	0.48	1.37	1.64	3.03**	0.74	2.91**
Hong Kong	7.24***	0.72	3.04**	1.65	2.90**	0.45	3.38**	1.03	1.42
Korea	9.21***	0.95	2.03	2.14*	3.99***	1.59	0.56	0.41	2.79**
Thailand	1.78	0.76	1.15	2.95**	4.00***	1.11	0.08	1.27	0.18
Singapore	2.92**	0.76	4.88***	4.93***	2.31	0.20	3.48**	1.69	0.79
Malaysia	0.52	0.62	1.81	3.58**	1.96	0.02	4.49***	1.35	1.54
Taiwan	5.66***	0.53	1.57	0.76	0.60	1.03	2.50*	1.25	3.36**
Phillipines	7.04***	0.23	1.10	2.91**	4.08***	2.95**	0.52	0.63	8.00***

* denotes significance at the 90% level, ** denotes significance at the 95% level, *** denotes significance at the 99% level

markets of the US, Hong Kong, Malaysia and the Phillipines. Similar results hold for the Hong Kong market. The analysis finds significant Granger causality for the S&P 500, the Nikkei and the Singapore FTSE index. Therefore the Hang Seng seems to be only influential for mature markets and does not significally influence the newly industrialized countries of East and South East Asia, a result which is consistent with Dekker et al. (1999).

The leading role in Asia seems to belong to Korea instead. Its stock price index is Granger causal for Thailand, Singapore, Malaysia and the Phillipines. The big influence of the KOSPI index is further bolstered as it is the only variable which helps to predict the US stock market on the 95% confidence level, while the Singapore stock market is only Granger causal at the 90% level. On the other hand, it reacts to short-run impulses only from the US, Thailand and the Phillipines. Together with the comparatively high estimate for the loading matrix, Korea appears to be the most integrated stock market of those in the system and highly interacts internationally.

The least influential market seems to be the Taiwanese one. The Weighted Index is not Granger causal for any other stock market in the system. In contrast, it reacts to influences from the US, Malaysia and the Phillipines. The Taiwanese market can therefore be classified as a follower that shares linkages to other markets, but is not influential enough to send significant impulses abroad.

The behavior of the stock markets over time to idiosyncratic errors in other markets in the system is depicted in the impulse response functions in Figure 4 and 5. They compare the IRFs obtained from the unrestricted VAR to the ones estimated from the VECM for a period of one year. It is clearly visible that the impulse responses from the vector error correction model converge quite quickly to the long-run equilibrium. In contrast, the IRFs from the unrestricted VAR do not converge to a steady value, but tend to have an influence even one year later. However, this is inconsistent with the concept of cointegration and the VAR impulse responses should only be used for short-term prediction. What the graphs do not show is that the VAR impulses die out in the very long run as they are unable to catch the restrictions of the cointegrating vector.

5.4 Structural Break

All the results above are based on the assumption that the data generating process remains constant during the whole period analysed. If structural breaks are present the estimated parameters might be biased and inconsistent. In the present data set which covers almost 15 years, a structural change is somewhat likely. I suspect that the financial crises covered by the data might alter the long-run relationship. Especially the Asian financial crisis of 1997/1998 might influence the cointegration structure. Indeed, graphical analysis shows

Figure 4: Impulse Response Functions VAR

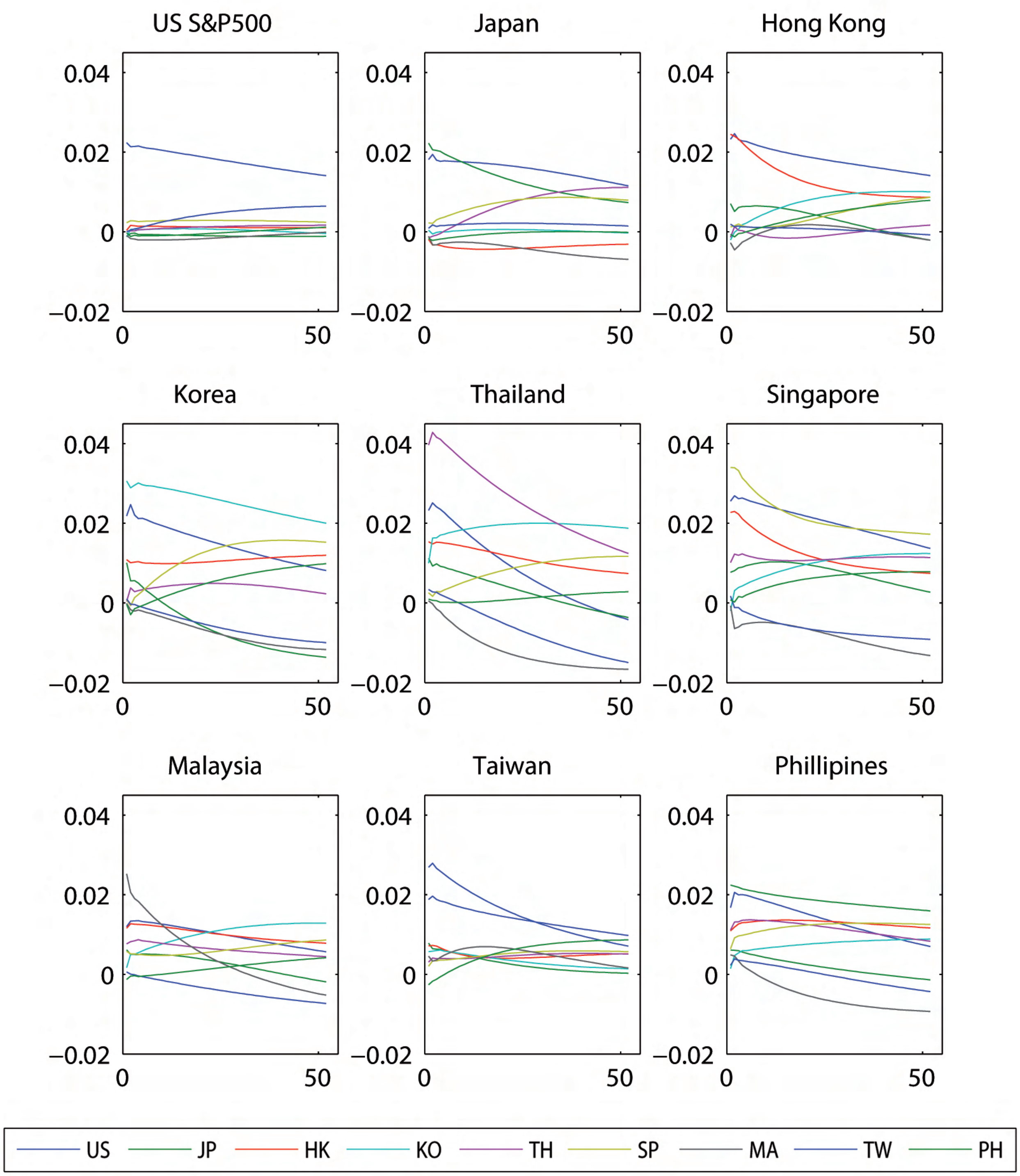
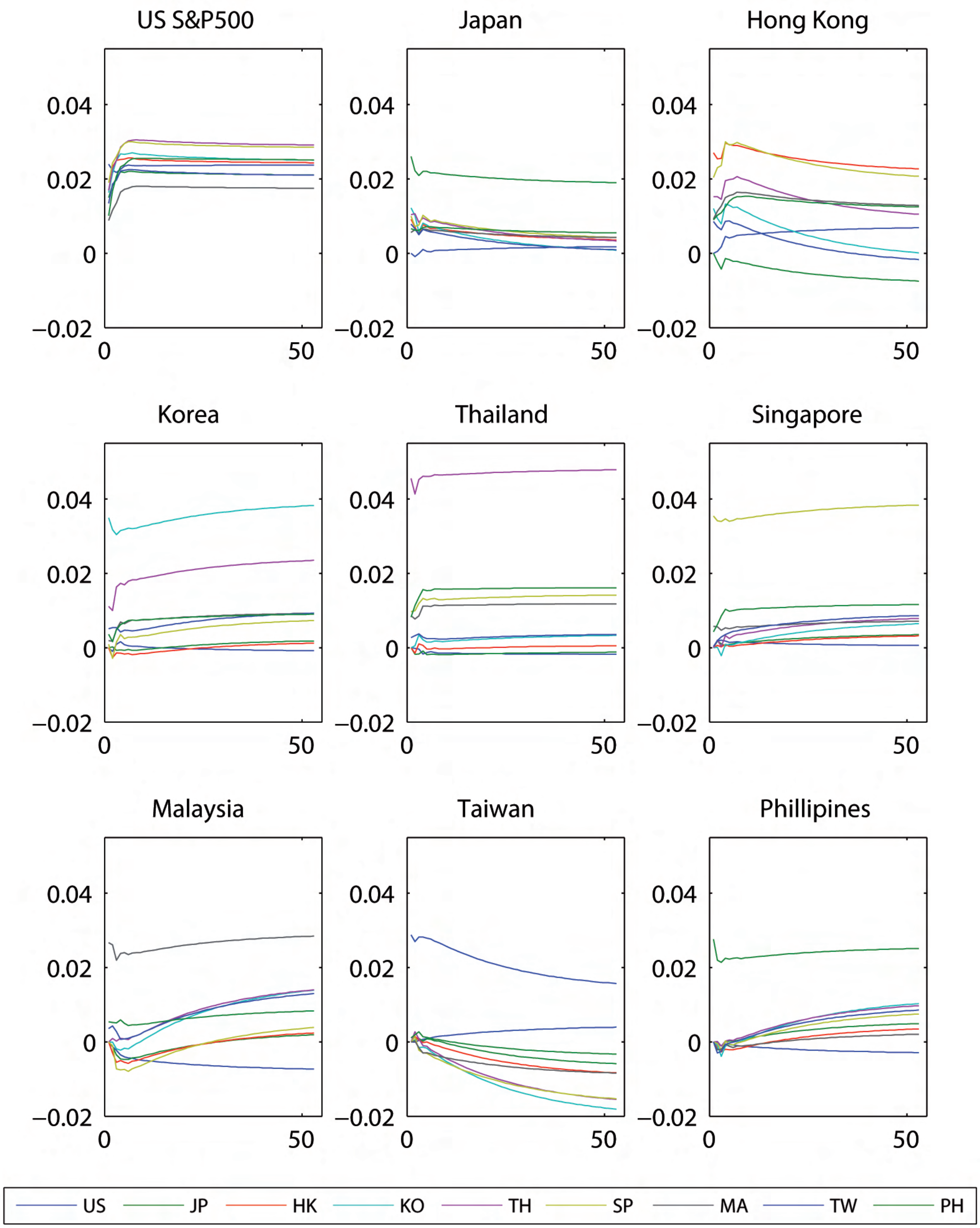


Figure 5: Impulse Response Functions VECM



heavy fluctuations during the years 1997/1998 which correspond to the periods 105-209 in the sample.

To formalize the analysis I perform the Gregory and Hansen (1996) cointegration test. This test allows to check for cointegration if there is a single structural break present in the data and can detect the possible break point. The test has been specified to account for a break in the intercept as well as in the slope coeffient, which corresponds to the regime shift model in equation (35). Again, the lag length for the mutual tests has been detected by downward testing and both the ADF^* and Z_t^* statistics are used. Results are reported in Table 9.

Accounting for a regime shift in the intercept and the slope, the Gregory and Hansen test indeed is able to detect cointegration relationships that could not be found by the standard CRADF test. These are the relationships US - Japan, US - Singapore, Malaysia - Phillipines, Korea - Phillipines, Hong Kong - Taiwan, and Hong Kong - Phillipines. The relationships US - Taiwan, Hong Kong - Korea, Korea - Malaysia, Hong Kong - Malaysia, Singapore - Phillipines and Taiwan - Phillipines were confirmed. In contrast, the Gregory and Hansen test is unable to detect the other relationships already found by the standard CRADF test. This indicates that these relationships do not experience any structural break and that the Gregory and Hansen test loses power if more regressors for the regime shift are included into the cointegrating relationship.

Of the newly detected cointegration relationships, only the two pairs US - Japan (October 1997) and US - Singapore (June/August 1997) experience a break during the Asian financial crisis. The other structural changes, Hong Kong - Phillipines, Korea - Phillipines (both July 1999), Malaysia - Phillipines (November 1999) and Hong Kong - Taiwan (January/February 2000) take place much later and are unlikely to be related to the crisis. The aforementioned two relationships linked to the Asian crisis will now be analysed in more detail.

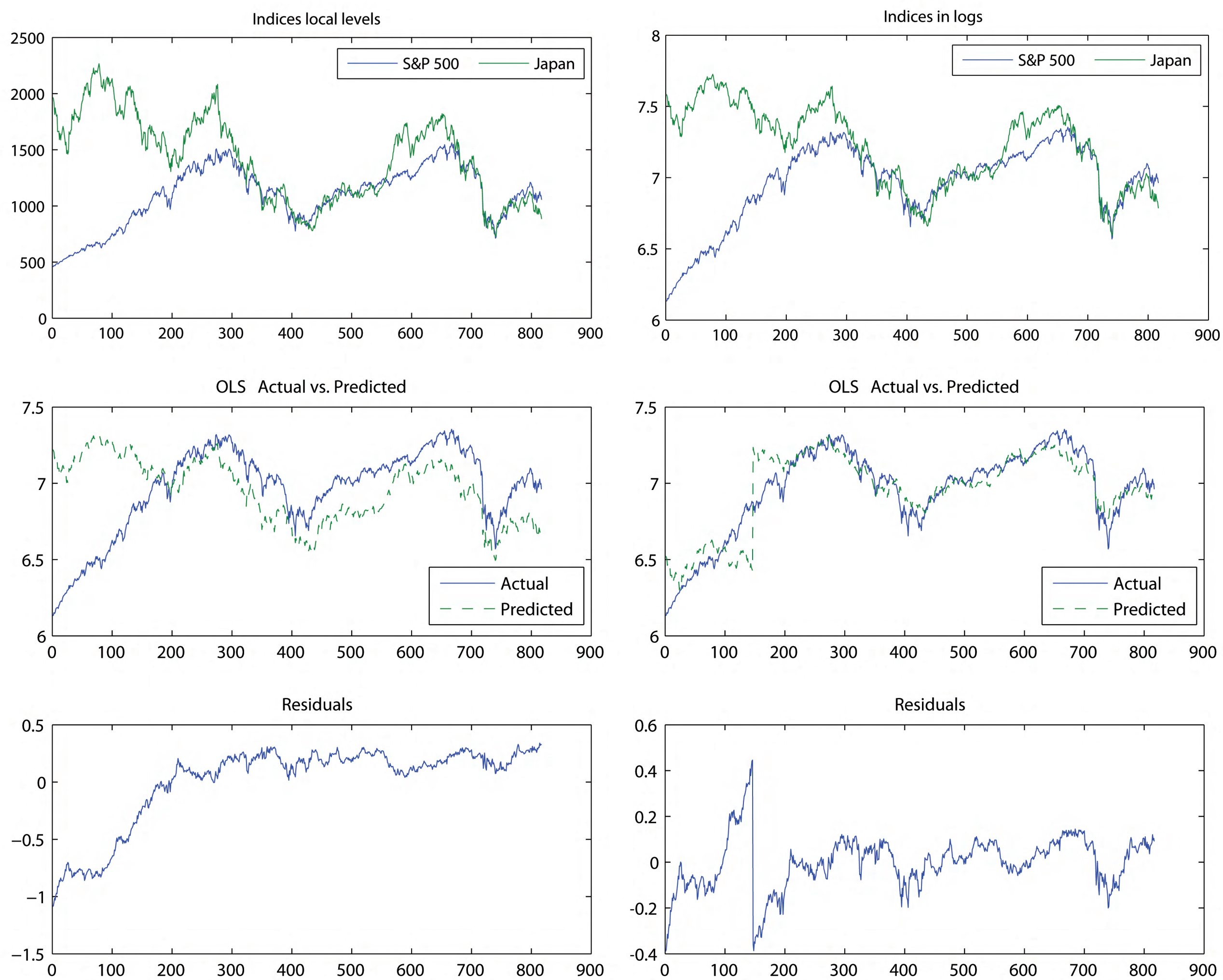
Figure 6 gives an example of a structural break using the S&P 500 and Nikkei 225 index. While the standard CRADF test could not reject the null of no cointegration, the

Gregory and Hansen test detected a long-run relationship under a regime shift at the 147th observation. The figure shows the actual versus the predicted value and the associated errors of the cointegration regression without (left) and with the inclusion of the time dummy variables (right). Comparing the two graphs it becomes clear why the CRADF test could not reject the null of a unit root present in the errors. At the beginning of the sample period, the Nikkei 225 denotes significantly higher than the S&P 500. While the American stock index grows rather smoothly over the first 300 periods, the Japanese market experiences heavy fluctuations with an average loss, resulting in the two stock markets approaching each other. After the break point, both indices move closer together and show similar patterns of ups and downs. Even though the Japanese market occasionally experiences higher growth than the US market, both stock price indices converge in the long run.

An economic interpretation of the results might be that an intitial long-run relationship was heavily disturbed by the Asian financial crisis, which happened around the sample points 105 - 209. While the Japanese market was heavily hit by the crisis, losing about 25% of its value, the US market seems to be invariant to the crisis and grew steadily. With the end of the crisis, which happened around observation 200, a new long-run cointegration relationship may have been formed between the two markets. This might be due to fundamental changes of the Japanese economy during the turbulences. Once this correction had been completed, both markets continue to follow a common trend on a now significantly altered level. Together with the results from the VECM and the Granger causality tests, it is likely that the US market dominates the relationship and the Japanese market adjusts to it, not the other way round. The same line of argumentation might explain the relationship US - Singapore, which exhibits very similar patterns.

In conclusion, the Gregory and Hansen (1996) test helps to find cointegration relationships under structural breaks which could not been detected by the Cointegration Regression ADF test. Of the five additional relationships, only two can be linked to the Asian inancial crisis of 1997/1998. Further analysis shows that this is most likely due to a different reaction

Figure 6: Constant parameters versus structural break



to the crisis. While the Asian markets drops sharply during that period, the US stock market remains mainly unchanged. This difference breaks up the old cointegration relationship which is followed by a new one.

5.5 Robustness Check

To check the main results for their robustness against changes in the denomination, I apply the same methodology to the US dollar data rather than the local currency denomi-

Table 9: Gregory and Hansen (1996) test results

	Japan		Hong Kong		Korea		Thailand		Singapore		Malaysia		Taiwan		Phillipines	
	ADF	PP	ADF	PP	ADF	PP	ADF	PP	ADF	PP	ADF	PP	ADF	PP	ADF	PP
US	-5.17**	-5.15**	-3.28	-3.19	-3.57	-3.58	-4.18	-3.88	-4.34*	-4.25	-3.39	-3.61	-4.59*	-4.57*	-4.21	-3.80
	147	146	150	151	220	227	363	358	136	130	132	137	192	192	315	125
JP			-2.43	-2.37	-2.68	-2.46	-2.80	-2.63	-3.30	-3.03	-2.77	-2.45	-2.84	-2.76	-3.59	-3.19
			326	325	327	324	327	354	329	324	327	325	352	351	694	685
HK					-4.34*	-4.16	-3.90	-3.49	-4.23	-3.98	-4.46*	-4.92**	-4.71**	-4.23	-4.90**	-4.53*
					364	151	574	593	234	131	137	126	269	274	237	235
KO							-3.86	-4.05	-3.44	-3.44	-4.70**	-5.00**	-3.71	-3.26	-4.38*	-4.33*
							175	226	241	241	175	132	279	275	237	246
TH									-3.96	-4.07	-3.83	-3.90	-3.82	-3.76	-3.77	-3.68
									398	405	125	130	301	303	366	356
SP											-3.84	-3.68	-3.85	-3.79	-4.34*	-4.22
											250	353	286	310	195	694
MA													-3.98	-3.06	-5.93***	-6.13***
													285	275	255	255
TW															-4.54*	-4.11
															315	304

* denotes significance at the 90% level, ** denotes significance at the 95% level, *** denotes significance at the 99% level

nation. For brevity, only the major results are summarized here. All testing and estimation results are reported in the Appendix.

The unit root tests do not differ in their results. Both the ADF and the Phillips-Perron test again cannot reject the null of a unit root in the stock prices, but reject non-stationarity for the differences at the 99% level. This suggests that both the dollar and local currency denominated indices follow $I(1)$ processes.

The CRADF tests based on the lags obtained by the Ng and Perron (1995) downtesting procedure find two significant cointegration relationships: Hong Kong - Taiwan at the 95% and Taiwan - Phillipines at the 90% significance level. Changing the lag length confirms these relationships and also detects a cointegrating vector between Japan and Hong Kong. If the test is specified to exclude a deterministic time trend, it also detects the relationships US - Korea, US - Taiwan, Hong Kong - Korea and Singapore - Malaysia. These are by and large the same relationships that were found using local currencies and there seem to be no structural differences between both datasets.

Using the VAR model for the dollar denominated data to find an appropriate lag length k for the Johansen procedure, the AIC suggests to include two lags, while the BIC is minimized for only one lagged value. The Johansen trace and maximum eigenvalue test reject the null of $r = 0$ at 99% and 95% respectively. This result is robust against changes in the choice of k. Again, the existence of a second cointegrating vector is not clear. While the trace statistic tends to reject the null of $r \leq 1$, the maximum eigenvalue statistic is unable to find more long-run relationships at any lags except for $k = 6$.

Performing the Granger causality F-tests, the result for dollar denominated data gives slightly different conclusions. The American stock market again seems to be the most influential one and the opposite is still true for Japan. In contrast, the Hong Kong market sees huge drops in its F-statistic for the American and Singapore market, losing its Granger causality for these indices. Instead, the Singapore index becomes more influential being additionally Granger causal for the Hong Kong, Korean and Thai market. This finding is consistent with Yang et al. (2003). As the strong results for the Korean KOSPI do not change, the Granger causality tests indicate that both Korea and Singapore are to some extent the market leaders in Asia when the denomination is changed to a common US dollar basis.

The Gregory and Hansen (1996) test applied to the dollar denominated data confirms the structural break for the relationship US - Japan even though it detects a slightly later (August 1997) break point. In contrast, any cointegration between the US and Singapore cannot be confirmed anymore. This suggests that the huge devaluation of the Southeast Asian currencies during the crisis had a significant effect on the cointegration relationship between the Singapore and the US stock market (Kamin, 1999). The same result holds for the pair Malaysia - Phillipines where the null of no cointegration cannot be rejected. Instead, the Gregory and Hansen test finds cointegration between Japan - Korea, yet the break point for September 1999 does not suggest any relation to the Asian financial crisis.

In summary, changing the denomination from local currencies to US dollar does, with some exceptions, not crucially change the previous results. The main conclusion taken from the analysis in local currencies is robust against a change of the currency unit. Especially, most of the cointegration results are still valid. However, the Gregory and Hansen test leads to some difference in testing cointegration under a structural break. In general, the test finds less relationships when applied on dollar data. This suggests that exchange rate fluctuations have some influence on long-run equilibria between international stock markets, but the effect is limited to those countries which suffered from devaluation of their currencies.

6 Conclusion

The analysis clearly shows that there are long-run relationships between the Asian markets and the US S&P 500 index for the sample period 1995-2010. Though the stock price indices all are non-stationary and seem to follow a random walk, they do interact with each other and have a stationary equilibrium relationship which assures that the stock indices never drift too far apart.

While the Cointegration Regression ADF test does not show much evidence for pairwise cointegration, the Johansen (1988) procedure unambigously concludes that there is at least one, possibly even two statistically significant cointegration vectors in the system. This result suggests that the cointegration structure is more complex than simple mutual relationships and that long-run equilibria are determined by more than two markets.

The estimation of the vector error correction model yields insight into short-term and long run linkages between the markets. Granger causality tests suggest that the US market is most influential in the short-run, being Granger causal for almost all the other countries in the system. The mature markets in Asia, Japan and Hong Kong, do not have great impact on the region which confirms the result of Yang et al. (2003). Surprisingly, the Korean market seems to be more influential instead, having a short-run impact on almost all the Southeast Asian markets and even on the US stock index.

Analysis of the cointegration vector found by the Johansen procedure confirms the leading position of the American market. The S&P 500 index is the only index which does not adjust to deviations from the long-run relationship. Instead, the burden of adjustment to any disequilibrium belongs to the Asian countries solely. Korea and Taiwan seem to react fastest to reduce the error, while the statistically not significant estimates for Malaysia and the Phillipines suggest that they hardly respond at all.

The Gregory and Hansen (1996) test providing cointegration testing under a single structural break shows that there are indeed regime shifts in the cointegration relationship between the markets. Some of these structural breaks can be linked to the Asian financial crisis, most significantly for the relationship between the US and Japan and US - Singapore. For the American-Japanese link this is due to very different reactions of both markets to the financial turbulences. It can be shown that the initial cointegration structure is disturbed by the crisis, and subsequently followed by a new one. This result is in line with the studies of Fernandez and Sosvilla (2001) and Wong et al. (2004) confirming the important effect of the Asian crisis.

Controlling the results for changes in the denomination of the stock market mostly confirms the previous results. Changing from a local currency to a common US dollar denomination shows that the index price series are still integrated of order one. The Cointegration Regression ADF test finds similar mutual cointegration results and the Johansen procedure also confirms the existence of a cointegrating vector when applied to the whole system of the nine markets.

Major changes only apply to the Granger causality tests which suggest that Hong Kong is less influential for predicting short term returns in other markets. Instead Singapore seems to be Granger causal for most of the Asian and even the US stock market. The Gregory and Hansen cointegration test applied to the dollar denominated data also confirms the major results, especially the structural break for the relationship US - Japan during the Asian financial crisis. Yet it is unable to detect cointegration for some countries which experienced huge drops in their exchange rate to the US dollar, most notably Singapore and Malaysia.

The implications for finance theory and practise are clear. With stock market cointegration present in the data, the efficient market hypothesis is violated. Both short-run and long-run linkages between the indices suggest that stock returns are not independent, but predictable using information of other markets. The results also suggest that investors who seek to diversify their portfolios internationally should be aware that the nine stock markets in the system follow a common stochastic trend. This means that these markets generate similar returns in the long-run. Therefore, diversification across the markets is limited and investors should include other markets with lower correlation to hedge their risk.

References

Banerjee, A., J. Dolado, J.W. Galbraith, and D.F. Hendry (1993): Co-Integration, Error Correction, and the Econometric Analysis of Non-Stationary Data, Oxford University Press.

Bessler, D. A. and J. Yang (2003): The Structure of Interdependence in International Stock Markets, *Journal of International Finance* 22, 261-287.

Blackman, S., K. Holden, and W. Thomas (1994): Long-term Relationships between International Share Prices, *Applied Financial Economics* 4, 297-304.

Bollerslev, T. (1986): Generalized Autoregressive Conditional Heteroskedasticity, *Journal of Econometrics* 31, 307-327.

Burke, S. and J. Hunter (2005): Modelling Non-Stationary Economic Time Series, Palgrave.

Chen, G., M. Firth, and O. Meng Rui (2000): Stock Market Linkages: Evidence from Latin America, *Journal of Banking & Finance* 26, 1113-1141.

Cochrane, J.H. (2005): Time Series for Macroeconomics and Finance, Chicago Graduate School of Business Lecture Notes.

Dekker, A., K. Sen, and M. Young (2001): Equity Market in The Asia Pacific Region: A Comparison of the Orthogonalized and Generalized VAR approaches, *Global Finance Journal* 12, 1-33.

Dickey, D.A. and W.A. Fuller (1979): Distribution of the Estimators for Autoregressive Time Series with a Unit Root, *Journal of the American Statistical Association* 74, 427431.

Enders, W. (1995): Applied Econometric Time Series, Wiley.

Engle, R. (1982): Autoregressive Conditional Heteroscedasticity with Estimates of Variance of United Kingdom Inflation, *Econometrica* 50, 987-1008

Fernandez-Serrano, J.L. and S. Sosvilla-Rivero (2001): Modelling Evolving Long-run Relationships: The Linkages between Stock Markets in Asia, *Japan and the World Economy* 13, 145-160.

Fu, R. and M. Pagani (2010): On the Cointegration of International Stock Indices, *Journal of Economics and Finance* 30, 1-18.

Engle, R.F. and C.W.J. Granger, (1987): Co-integration and Error-Correction: Representation, Estimation and Testing, *Econometrica* 55, 251-276.

Granger, C.W.J. (1981): Some Properties of Time Series Data and Their Use in Econometric Model Specification, *Journal of Econometrics* 16, 121-130.

Granger, C.W.J. and A. Weiss (1983): Time Series Analysis of Error-Correcting Models, in: Karlin, S.: Studies in Econometrics, Time Series, and Multivariate Analysis, Academic Press, 255-278.

Granger, C.W.J and O. Morgenstern (1970): Predictability of Stock Market Prices, Heath Lexington.

Gregory, A.W. and B.E. Hansen (1996): Residual-based Tests for Cointegration in Models with Regime Shifts, *Journal of Econometrics* 70, 99-126.

Gregory, A.W., J.M. Nason, and D.G. Watt (1996): Testing for Structural Breaks in Cointegrated Relationships, *Journal of Econometrics* 71, 321-241.

Jarque, C.M. and A.K. Bera (1987): A Test for Normality of Observations and Regression Residuals, *International Statistical Review* 55, 163-172.

Johansen, S. (1988): Statistical Analysis of Cointegration Vectors, *Journal of Economic Dynamics and Control* 12, 231-254.

Johansen, S. (1991): Estimation and Hypothesis Testing of Cointegration Vectors in Gaussian Vector Autoregressive Models, *Econometrica* 59, 1551-1580.

Kamin, S.B. (1999): The Current International Financial Crisis: How Much is New?, *Journal of International Money and Finance* 18, 501-514.

Kasa, K. (1992): Common Stochastic Trends in International Stock Markets, *Journal of Monetary Economics* 29, 95-124.

Koop, G. (1994): An Objective Bayesian Analysis of Common Stochastic Trends in International Stock Prices and Exchange Rates, *Journal of Empirical Finance* 1, 343-364.

Koop, G., M.H. Pesaran and S.M. Potter (1996): Impulse Response Analysis in Nonlinear Multivariate Models, *Journal of Econometrics* 74, 119-147.

LeSage, J.P (1999): Applied Econometrics using MATLAB, Working Paper.

Lim, L.K. (2007): Linkages between ASEAN Stock Markets: A Cointegration Approach, Working Paper.

Luetkepohl, H. (2005): New Introduction to Multiple Time Series Analysis, Springer.

Luetkepohl, H. and M. Kraetzig (2004): Applied Time Series Econometrics, Cambridge University Press.

Luetkepohl, H. and H. Reimers (1992): Impulse Response Analysis of Cointegrated Systems, *Journal of Economic Dynamics and Control* 16, 53-78.

Masih, A.M.M. and R. Masih (1997): A Comparative Analysis of the Propagation of Stock Market Fluctuations in Alternative Models of Dynamic Causal Linkages, *Applied Financial Economics* 7, 59-74.

Masih, A.M.M. and R. Masih (2001): Long and Short Term Dynamic Causal Transmission amongst International Stock Markets, *Journal of International Money and Finance* 20, 563-587.

Maysami, R.C. and T.S. Koh (2000): A Vector Error Correction Model of the Singapore Stock Market, *International Review of Economics and Finance* 9, 79-96.

MacKinnon, J.G.: (1996): Numerical Distribution Functions for Unit Root and Cointegration Tests, *Journal of Econometrics* 11, 601-618.

Mitchell, J. (2000): The importance of long run structure for impulse response analysis in VAR models, *NIESR Discussion Papers* 172.

Naka A. and D. Tufte (1997): Examining impulse response functions in cointegrated systems, *Applied Economics* 29, 1593-1603.

Narayan, P.K. and R. Smyth (2005): Cointegration of Stock Markets between New Zealand, Australia and the G7 Economies: Searching for Co-Movement under Structural Change, *Australian Economic Papers* 44, 231-247.

Ng, S. and P. Perron (1995): Unit Root Tests in ARMA Models with Data-Dependent Methods for the Selection of the Truncation Lag, *Journal of the American Statistical Association* 90, 268-281.

Panto, D.B., V.P. Lessig, and M. Joy (1976): Comovement of International Equity Markets: A Taxonomic Approach, *Journal of Financial and Quantitative Analysis* 11, 415-432.

Phillips, P.C.B. and P. Perron (1988): Testing for a Unit Root in Time Series Regression, *Biometrika* 75, 335-346.

Phillips, P.C.B. (1998): Impulse Response and Forecast Error Variance Asymptotics in Nonstationary VARs, *Journal of Econometrics* 83, 21-56.

Ripley, D.M. (1973): Systematic Elements in the Linkage of National Stock Market Indices, *Review of Economics and Statistics 55*, 356-361.

Sheng, H.C. and A.H. Tu (2000): A study of cointegration and variance decomposition among national equity indices before and during the period of the Asian financial crisis, *Journal of Multinational Financial Management* 10, 345-365.

Schwert, G.W. (1989): Tests for Unit Roots: A Monte Carlo Investigation, *Journal of Business & Economic Statistics* 7, 147-160.

Siklos, P.L and P. Ng (2001): Integration among Asia-Pacific and International Stock Markets: Common Stochastic Trends and Regime Shifts, *Pacific Economic Review* 6, 89-110.

Stock, J.H. (1987): Asymptotic Properties of Least Squares Estimators of Cointegrating Vectors, *Econometrica* 55, 1035-1056.

Tsay, R.S. (2005): Analysis of Financial Time Series, Second Edition, Wiley.

Voronkova, S. (2004): Equity Market Integration in Central European Emerging Markets: A Cointegration Analysis with Shifting Regimes, *International Review of Financial Analysis* 13, 633-647.

Watson, M.W. (1994): "'Vector autoregressions and cointegration"'. In *Handbook of Econometrics*, Volume IV (eds. Engle, R.F. and McFadden, D.L.), Elsevier Science B.V.

Wong, W., J. Penm, R.D. Terrell, and K. Lim (2004): The Relationship Between Stok Markets of Major Developed Countries and Asian Emerging Markets, *Journal of Applied Mathematics and Decision Sciences* 8, 201-218.

Yang, J., J. Kolari, and I. Min (2003): Stock Market Integration and Financial Crises. The Case of Asia, *Applied Financial Economics* 13, 477-486.

Appendix

OLS Consistency under cointegration

The OLS estimate for β is

$$
\begin{aligned}
\tilde{\beta} &= (X'X)^{-1}(X'Y) = (\sum_t x_t^2)^{-1}\left(\sum_t x_t(\alpha x_t + u_t)\right) \\
&= \alpha + \sum_t x_t u_t / \sum_t x_t^2 = \alpha + \frac{\frac{1}{T}\sum_t x_t u_t}{\frac{1}{T}\sum_t x_t^2}
\end{aligned} \tag{42}
$$

where the last term is of interest. Applying the Weak Law of Large Numbers to this term, we see that

$$\frac{1}{T}\sum_t x_t u_t \xrightarrow{p} COV(x_t u_t) \tag{43}$$

$$\frac{1}{T}\sum_t x_t^2 \xrightarrow{p} VAR(x_t) \tag{44}$$

where the quotient is different from zero if there is correlation between x_t and u_t. However, if x_t is a unit root process such that $x_t = \sum_{i=1}^{t} \epsilon_t$, for big T, the variance of x_t will go to infinity as

$$
\begin{aligned}
E[x_t^2] &= E\left(\sum_{i=1}^{t} \epsilon_t\right)^2 \\
&= E[(\epsilon_1 + \epsilon_2 + \epsilon_3 + \cdots)(\epsilon_1 + \epsilon_2 + \epsilon_3 + \cdots)] \\
&= E[(\epsilon_1^2 + \epsilon_2^2 + \epsilon_3^2 + \cdots)] \\
&= t\sigma^2
\end{aligned} \tag{45}
$$

This term goes to infinity as $t \to \infty$. Therefore, with increasing sample size the last term in (42) will go to zero and the OLS estimator $\tilde{\beta}$ will converge to the true value even if there is correlation between the regressors and the error term.

Statistical Tables

Table 10: Variance Covariance matrix of logged indices

	US	JP	HK	KO	TH	SP	MA	TW	PH
US SP500	0.08	-0.01	0.05	0.04	-0.07	-0.01	0.00	0.03	-0.01
Japan	-0.01	0.08	0.00	-0.02	0.06	0.07	0.02	0.03	0.05
Hong Kong	0.05	0.00	0.09	0.11	0.04	0.07	0.06	0.04	0.06
Korea	0.04	-0.02	0.11	0.21	0.12	0.11	0.10	0.02	0.09
Thailand	-0.07	0.06	0.04	0.12	0.29	0.18	0.12	0.02	0.14
Singapore	-0.01	0.07	0.07	0.11	0.18	0.18	0.10	0.04	0.13
Malaysia	0.00	0.02	0.06	0.10	0.12	0.10	0.08	0.02	0.08
Taiwan	0.03	0.03	0.04	0.02	0.02	0.04	0.02	0.05	0.04
Phillipines	-0.01	0.05	0.06	0.09	0.14	0.13	0.08	0.04	0.12

Table 11: CRADF test results for US dollar denomination

	JP	HK	KO	TH	SP	MA	TW	PH
US SP500	-2.20	-1.82	-2.21	-2.80	-2.34	-2.74	-2.28	-2.46
Japan		-3.06	-2.76	-2.39	-3.39	-1.86	-2.53	-2.87
Hong Kong			-2.78	-2.76	-3.23	-2.51	-3.94**	-3.13
Korea				-2.43	-2.87	-2.82	-2.11	-2.40
Thailand					-2.12	-2.45	-1.71	-1.86
Singapore						-2.33	-2.17	-3.32
Malaysia							-1.62	-2.11
Taiwan								-3.78*

* denotes significance at the 90% level, ** denotes significance at the 95% level, *** denotes significance at the 99% level

Table 12: Johansen test for dollar denomination

Trace Test		**Critical Values**		
H_0	λ_{trace}	**90%**	**95%**	**99%**
$r = 0$	225.82	190.87	197.38	210.04
$r \leq 1$	164.44	153.63	159.53	171.09
$r \leq 2$	113.22	120.37	125.62	135.98
$r \leq 3$	76.10	91.11	95.75	104.96
$r \leq 4$	50.11	65.82	69.82	77.82
$r \leq 5$	30.22	44.49	47.86	54.68
$r \leq 6$	17.83	27.07	29.80	35.46
$r \leq 7$	8.58	13.43	15.49	19.94
$r \leq 8$	2.21	2.71	3.84	6.64

Max Eigenvalue		**Critical Values**		
H_0	λ_{max}	**90%**	**95%**	**99%**
$r = 0$	61.38	55.24	58.43	65.00
$r \leq 1$	51.23	49.29	52.36	58.66
$r \leq 2$	37.11	43.30	46.23	52.31
$r \leq 3$	26.00	37.28	40.08	45.87
$r \leq 4$	19.89	31.24	33.88	39.37
$r \leq 5$	12.39	25.12	27.59	32.72
$r \leq 6$	9.25	18.89	21.13	25.87
$r \leq 7$	6.37	12.30	14.26	18.52
$r \leq 8$	2.21	2.71	3.84	6.64

Table 13: Gregory and Hansen (1996) test results for US dollar denomination

	Japan		**Hong Kong**		**Korea**		**Thailand**		**Singapore**		**Malaysia**		**Taiwan**		**Phillipines**	
	ADF	PP	ADF	PP	ADF	PP	ADF	PP	ADF	PP	ADF	PP	ADF	PP	ADF	PP
US	-4.87**	-4.75**	-2.74	-2.89	-3.25	-3.30	-3.50	-3.24	-3.78	-3.66	-3.27	-3.25	-4.36*	-4.34*	-3.72	-3.62
	136	136	136	135	124	125	490	125	136	137	133	125	158	148	136	135
JP			-3.58	-3.49	-4.90**	-4.72**	-3.27	-3.26	-4.34*	-4.17	-3.34	-3.46	-3.53	-3.60	-3.44	-3.31
			296	294	344	341	325	325	329	324	315	325	125	122	690	658
HK					-3.97	-3.51	-3.85	-3.45	-4.36*	-4.16	-4.51*	-4.77**	-4.72**	-4.80**	-4.60*	-4.29
					633	593	596	130	140	127	137	127	277	292	245	235
KO							-4.31	-4.28	-4.28	-4.23	-4.37*	-4.47*	-2.67	-2.50	-4.08	-3.97
							151	193	241	248	179	192	535	533	246	246
TH									-2.75	-2.91	-3.52	-3.50	-2.22	-2.18	-2.40	-2.33
									134	130	245	252	122	130	328	350
SP											-3.47	-3.16	-2.77	-2.44	-4.95**	-4.70**
											250	253	127	122	270	280
MA													-1.93	-1.82	-3.55	-3.57
													323	125	259	260
TW															-4.55*	-3.78
															135	122

* denotes significance at the 90% level, ** denotes significance at the 95% level, *** denotes significance at the 99% level

Table 14: Results for VECM with three lags

Dependent variable	**US S&P500**		**Japan**		**Hong Kong**	
Variable	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
$SP500_{t-1}$	-0.044	-1.00	0.253***	4.54	0.248***	3.91
$SP500_{t-2}$	-0.062	-1.36	0.204***	3.58	0.147**	2.26
$SP500_{t-3}$	-0.057	-1.26	0.063	1.11	-0.070	-1.08
$Japan_{t-1}$	-0.035	-0.98	-0.109**	-2.43	-0.033	-0.65
$Japan_{t-2}$	-0.003	-0.07	-0.007	-0.15	-0.062	-1.23
$Japan_{t-3}$	-0.007	-0.19	-0.004	-0.08	0.026	0.52
$HongKong_{t-1}$	-0.003	-0.08	-0.072	-1.49	0.011	0.20
$HongKong_{t-2}$	-0.003	-0.08	-0.032	-0.66	0.014	0.24
$HongKong_{t-3}$	0.107***	2.77	0.122**	2.52	0.166***	3.02
$Korea_{t-1}$	-0.023	-0.91	0.019	0.59	-0.074	-2.03
$Korea_{t-2}$	0.061**	2.38	-0.026	-0.82	0.026	0.72
$Korea_{t-3}$	0.032	1.24	-0.019	-0.57	-0.006	-0.15
$Thailand_{t-1}$	-0.009	-0.46	-0.030	-1.15	-0.009	-0.30
$Thailand_{t-2}$	-0.001	-0.07	0.024	0.93	0.085***	2.87
$Thailand_{t-3}$	-0.029	-1.39	0.036	1.40	0.012	0.39
$Singapore_{t-1}$	0.060**	2.42	0.063	2.03	0.040	1.14
$Singapore_{t-2}$	0.024	0.96	-0.005	-0.16	-0.003	-0.08
$Singapore_{t-3}$	0.000	-0.01	-0.028	-0.90	0.004	0.11
$Malaysia_{t-1}$	-0.037	-1.14	-0.051**	-1.25	-0.123***	-2.64
$Malaysia_{t-2}$	-0.029	-0.88	-0.097	-2.37	-0.082	-1.76
$Malaysia_{t-3}$	-0.045	-1.38	-0.064	-1.55	0.007	0.15
$Taiwan_{t-1}$	-0.013	-0.43	0.034	0.94	0.068	1.63
$Taiwan_{t-2}$	0.010	0.35	0.044	1.20	-0.012	-0.28
$Taiwan_{t-3}$	0.003	0.11	-0.007	-0.19	-0.026	-0.63
$Phillipines_{t-1}$	-0.004	-0.13	-0.078**	-2.01	-0.060	-1.36
$Phillipines_{t-2}$	-0.028	-0.93	-0.051	-1.33	-0.077**	-1.75
$Phillipines_{t-3}$	0.045	1.52	0.065*	1.73	-0.010	-0.25
ec term SP500	0.002**	2.16	-0.003***	-3.10	-0.003**	-2.47
constant	-0.035**	-2.10	0.064***	3.03	0.060**	2.50

* denotes significance at the 90% level, ** denotes significance at the 95% level, *** denotes significance at the 99% level

Table 15: Results for VECM with three lags (continued)

Dependent variable	**Korea**		**Thailand**		**Singapore**	
Variable	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
$SP500_{t-1}$	0.290***	3.71	0.205**	2.08	0.227***	2.59
$SP500_{t-2}$	0.332***	4.15	0.131	1.30	0.064	0.71
$SP500_{t-3}$	0.015	0.19	0.030	0.30	-0.086	-0.97
$Japan_{t-1}$	-0.011	-0.17	0.014	0.17	-0.106	-1.51
$Japan_{t-2}$	-0.105*	-1.68	-0.108	-1.37	-0.003	-0.04
$Japan_{t-3}$	-0.017	-0.27	-0.051	-0.65	-0.003	-0.04
$HongKong_{t-1}$	-0.014	-0.21	0.019	0.22	0.190**	2.49
$HongKong_{t-2}$	0.045	0.65	-0.069	-0.80	0.029	0.38
$HongKong_{t-3}$	0.163**	2.40	0.137	1.60	0.223***	2.94
$Korea_{t-1}$	-0.101**	-2.26	-0.015	-0.26	-0.120**	-2.39
$Korea_{t-2}$	-0.058	-1.30	0.164***	2.90	0.134***	2.67
$Korea_{t-3}$	0.004	0.10	0.034	0.59	0.041	0.81
$Thailand_{t-1}$	0.026	0.71	-0.105**	-2.30	0.024	0.58
$Thailand_{t-2}$	0.123***	3.37	0.103**	2.24	0.104**	2.54
$Thailand_{t-3}$	-0.011	-0.29	0.014	0.30	0.040	0.99
$Singapore_{t-1}$	0.007	0.17	0.051	0.93	-0.031	-0.63
$Singapore_{t-2}$	-0.062	-1.42	-0.052	-0.96	0.019	0.39
$Singapore_{t-3}$	0.064	1.49	0.057	1.06	0.006	0.11
$Malaysia_{t-1}$	-0.029	-0.50	0.002	0.03	-0.056	-0.88
$Malaysia_{t-2}$	-0.059	-1.03	-0.017	-0.23	-0.200***	-3.11
$Malaysia_{t-3}$	-0.040	-0.69	0.032	0.43	-0.024	-0.37
$Taiwan_{t-1}$	0.046	0.88	0.110*	1.69	0.063	1.08
$Taiwan_{t-2}$	-0.024	-0.46	-0.029	-0.45	-0.106*	-1.82
$Taiwan_{t-3}$	0.017	0.33	-0.059	-0.91	-0.042	-0.73
$Phillipines_{t-1}$	-0.059	-1.08	-0.014	-0.20	-0.027	-0.44
$Phillipines_{t-2}$	-0.144***	-2.66	-0.044	-0.64	-0.078	-1.28
$Phillipines_{t-3}$	0.032	0.60	0.017	0.26	0.039	0.66
ec term SP500	-0.007***	-4.48	-0.004**	-2.07	-0.003*	-1.93
constant	0.133***	4.49	0.076**	2.04	0.064*	1.91

* denotes significance at the 90% level, ** denotes significance at the 95% level, *** denotes significance at the 99% level

Table 16: Results for VECM with three lags (continued)

Dependent variable	**Malaysia**		**Taiwan**		**Phillipines**	
Variable	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
$SP500_{t-1}$	0.055	0.92	0.252***	3.93	0.259***	4.16
$SP500_{t-2}$	0.059	0.98	0.120*	1.83	0.161**	2.53
$SP500_{t-3}$	0.020	0.33	0.057	0.87	0.083	1.31
$Japan_{t-1}$	0.011	0.23	-0.014	-0.27	-0.016	-0.32
$Japan_{t-2}$	-0.062	-1.32	-0.050	-0.98	-0.039	-0.78
$Japan_{t-3}$	-0.010	-0.20	0.036	0.71	-0.009	-0.19
$HongKong_{t-1}$	0.105**	2.03	-0.038	-0.67	0.025	0.46
$HongKong_{t-2}$	0.059	1.14	-0.037	-0.65	-0.091*	-1.67
$HongKong_{t-3}$	0.029	0.56	0.107*	1.92	-0.031	-0.57
$Korea_{t-1}$	0.002	0.07	0.017	0.47	-0.071**	-1.99
$Korea_{t-2}$	0.096***	2.82	-0.010	-0.26	0.070**	1.97
$Korea_{t-3}$	0.063*	1.84	-0.051	-1.37	0.013	0.35
$Thailand_{t-1}$	-0.006	-0.22	0.023	0.78	0.083***	2.88
$Thailand_{t-2}$	0.057**	2.04	0.030	1.00	0.064**	2.21
$Thailand_{t-3}$	0.041	1.48	-0.015	-0.49	0.031	1.06
$Singapore_{t-1}$	0.007	0.21	0.050	1.40	0.073**	2.12
$Singapore_{t-2}$	-0.002	-0.06	0.033	0.93	0.064*	1.86
$Singapore_{t-3}$	0.002	0.07	0.025	0.71	0.045	1.32
$Malaysia_{t-1}$	-0.010	-0.24	0.035	0.74	0.027	0.60
$Malaysia_{t-2}$	-0.135***	-3.11	-0.073	-1.56	0.013	0.29
$Malaysia_{t-3}$	0.083*	1.89	-0.097**	-2.04	0.051	1.11
$Taiwan_{t-1}$	0.012	0.30	-0.039	-0.92	0.037	0.91
$Taiwan_{t-2}$	-0.059	-1.50	0.064	1.52	0.031	0.76
$Taiwan_{t-3}$	-0.055	-1.40	0.033	0.78	-0.030	-0.74
$Phillipines_{t-1}$	-0.079*	-1.93	-0.128***	-2.89	-0.206***	-4.77
$Phillipines_{t-2}$	-0.007	-0.17	-0.028	-0.63	-0.060	-1.38
$Phillipines_{t-3}$	0.036	0.91	0.053	1.22	0.031	0.74
ec term SP500	-0.001	-0.62	-0.005***	-3.81	-0.001	-0.61
constant	0.014	0.63	0.092***	3.81	0.015	0.62

* denotes significance at the 90% level, ** denotes significance at the 95% level, *** denotes significance at the 99% level

Table 17: Results for VECM with two lags and dollar denomination

Dependent variable	**US S&P500**		**Japan**		**Hong Kong**	
Variable	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
$SP500_{t-1}$	-0.044	-1.02	0.206***	3.69	0.231***	3.71
$SP500_{t-2}$	-0.076*	-1.75	0.142**	2.52	0.122*	1.94
$Japan_{t-1}$	-0.004	-0.11	-0.092**	-2.13	0.048	1.00
$Japan_{t-2}$	-0.003	-0.10	-0.008	-0.18	-0.020	-0.42
$HongKong_{t-1}$	-0.013	-0.34	-0.032	-0.65	-0.036	-0.66
$HongKong_{t-2}$	-0.001	-0.02	-0.012	-0.24	-0.034	-0.62
$Korea_{t-1}$	-0.030	-1.45	0.028	1.06	-0.090***	-3.01
$Korea_{t-2}$	0.057***	2.73	0.022	0.80	0.011	0.38
$Thailand_{t-1}$	-0.006	-0.32	-0.014	-0.57	-0.004	-0.15
$Thailand_{t-2}$	0.001	0.07	0.010	0.41	0.069**	2.46
$Singapore_{t-1}$	0.055**	2.30	0.051*	1.65	0.077**	2.23
$Singapore_{t-2}$	0.012	0.52	-0.030	-0.96	0.020	0.59
$Malaysia_{t-1}$	-0.018	-0.72	-0.042	-1.27	-0.071*	-1.92
$Malaysia_{t-2}$	-0.001	-0.02	-0.018	-0.55	-0.039	-1.07
$Taiwan_{t-1}$	-0.013	-0.48	0.022	0.62	0.064	1.61
$Taiwan_{t-2}$	0.006	0.24	0.018	0.52	-0.012	-0.31
$Phillipines_{t-1}$	-0.006	-0.23	-0.036	-1.08	-0.076**	-2.04
$Phillipines_{t-2}$	-0.047*	-1.83	-0.088***	-2.65	-0.063*	-1.72
ec term SP500	0.003***	3.35	-0.002	-1.62	-0.003**	-2.52
constant	0.050***	3.42	-0.032*	-1.68	-0.052**	-2.47

* denotes significance at the 90% level, ** denotes significance at the 95% level, *** denotes significance at the 99% level

Table 18: Results for VECM with two lags and dollar denomination (continued)

Dependent variable	**Korea**		**Thailand**		**Singapore**	
Variable	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
$SP500_{t-1}$	0.379***	3.93	0.185*	1.78	0.198**	2.18
$SP500_{t-2}$	0.376***	3.88	0.037	0.35	-0.010	-0.11
$Japan_{t-1}$	0.024	0.32	0.094	1.17	0.011	0.15
$Japan_{t-2}$	-0.048	-0.65	0.039	0.48	0.129*	1.85
$HongKong_{t-1}$	-0.163*	-1.93	-0.035	-0.38	0.114	1.43
$HongKong_{t-2}$	-0.076	-0.90	-0.115	-1.26	-0.017	-0.22
$Korea_{t-1}$	-0.127***	-2.74	-0.002	-0.03	-0.107**	-2.46
$Korea_{t-2}$	0.034	0.73	0.141***	2.80	0.084*	1.91
$Thailand_{t-1}$	0.055	1.27	-0.135***	-2.90	0.033	0.81
$Thailand_{t-2}$	0.118***	2.74	0.104**	2.22	0.097**	2.40
$Singapore_{t-1}$	0.096*	1.79	0.114*	1.96	0.041	0.82
$Singapore_{t-2}$	-0.062	-1.15	-0.045	-0.78	0.032	0.63
$Malaysia_{t-1}$	-0.027	-0.47	-0.034	-0.55	-0.082	-1.53
$Malaysia_{t-2}$	0.006	0.10	-0.026	-0.42	-0.073	-1.35
$Taiwan_{t-1}$	0.056	0.91	0.116*	1.74	0.083	1.43
$Taiwan_{t-2}$	-0.072	-1.18	-0.037	-0.55	-0.118**	-2.06
$Phillipines_{t-1}$	-0.029	-0.50	0.058	0.93	-0.050	-0.92
$Phillipines_{t-2}$	-0.156***	-2.74	-0.029	-0.47	-0.082	-1.53
ec term SP500	-0.003	-1.28	-0.003	-1.29	-0.004**	-2.46
constant	-0.042	-1.28	-0.046	-1.31	-0.075**	-2.45

* denotes significance at the 90% level, ** denotes significance at the 95% level, *** denotes significance at the 99% level

Table 19: Results for VECM with two lags and dollar denomination (continued)

Dependent variable	**Malaysia**		**Taiwan**		**Phillipines**	
Variable	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
$SP500_{t-1}$	0.033	0.45	0.254***	3.75	0.298***	4.09
$SP500_{t-2}$	-0.018	-0.24	0.101	1.48	0.114	1.55
$Japan_{t-1}$	-0.006	-0.10	0.002	0.03	0.007	0.12
$Japan_{t-2}$	0.105*	1.88	-0.024	-0.46	0.035	0.63
$HongKong_{t-1}$	0.109*	1.70	-0.024	-0.40	0.001	0.02
$HongKong_{t-2}$	-0.011	-0.18	-0.046	-0.78	-0.134**	-2.10
$Korea_{t-1}$	0.001	0.04	-0.023	-0.71	-0.038	-1.10
$Korea_{t-2}$	0.091***	2.60	0.011	0.35	0.078**	2.23
$Thailand_{t-1}$	-0.011	-0.34	0.021	0.71	0.088***	2.70
$Thailand_{t-2}$	0.076**	2.34	0.052*	1.71	0.082**	2.51
$Singapore_{t-1}$	0.018	0.43	0.071*	1.87	0.074*	1.83
$Singapore_{t-2}$	-0.056	-1.38	0.040	1.05	0.052	1.28
$Malaysia_{t-1}$	0.003	0.08	0.050	1.24	-0.003	-0.07
$Malaysia_{t-2}$	-0.126***	-2.93	-0.059	-1.48	-0.009	-0.22
$Taiwan_{t-1}$	0.034	0.74	-0.026	-0.61	0.029	0.63
$Taiwan_{t-2}$	-0.022	-0.47	0.043	1.01	0.042	0.91
$Phillipines_{t-1}$	-0.091**	-2.09	-0.119***	-2.95	-0.191***	-4.40
$Phillipines_{t-2}$	0.003	0.06	-0.060	-1.49	-0.021	-0.48
ec term SP500	-0.002	-1.45	-0.004***	-2.93	0.001	0.99
constant	-0.035	-1.43	-0.067***	-2.94	0.024	0.97

* denotes significance at the 90% level, ** denotes significance at the 95% level, *** denotes significance at the 99% level